2021-03

APPLYING PREDICTIVE ANALYTICS IN ASSESSING HEALTH CONDITIONS OF APPLICANTS

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http://hdl.handle.net/10945/67146

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

APPLYING PREDICTIVE ANALYTICS IN ASSESSING HEALTH CONDITIONS OF APPLICANTS

by

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March 2021

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REPORT DOCUMENTATION PAGE			*Form Approved OMB No. 0704-0188*
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington, DC 20503.			
1. AGENCY USE ONLY ***(Leave blank)***	**2. REPORT DATE** March 2021	**3. REPORT TYPE AND DATES COVERED** Master's thesis	
4. TITLE AND SUBTITLE APPLYING PREDICTIVE ANALYTICS IN ASSESSING HEALTH CONDITIONS OF APPLICANTS			**5. FUNDING NUMBERS**
6. AUTHOR(S) Mark A. Knutson			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A			**10. SPONSORING / MONITORING AGENCY REPORT NUMBER**
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.			**12b. DISTRIBUTION CODE** A

13. ABSTRACT (maximum 200 words)

Predicting military attrition due to conditions that existed prior to service is a complicated problem. My thesis explores underwriting practices and risk assessment in the life and health insurance industries with the aim to link private sector underwriting techniques to the military medical screening process. I review the current prediction models in the economic, actuary, and medical fields and find many of these models utilize complicated machine-learning algorithms to include random forests, deep convolutional neural networks, and deep dynamic memory neural network models. For my empirical analysis, I utilize a Cox proportional hazard model to determine risk via potential predictor variables. My findings suggest past self-inflicted injuries, substance use disorder (current and in the past), waivers for drug offenses, missing an Armed Forces Qualification Test (AFQT) score, and deployments (current and in the past) are associated with higher hazard rates of separation. This information provides insights regarding the separation risks associated with various indicators.

14. SUBJECT TERMS logistic, predictions, attrition, medical, pre-existing conditions, MEPS			**15. NUMBER OF PAGES** 103
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	**18. SECURITY CLASSIFICATION OF THIS PAGE** Unclassified	**19. SECURITY CLASSIFICATION OF ABSTRACT** Unclassified	**20. LIMITATION OF ABSTRACT** UU

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

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MASTER OF SCIENCE IN MANAGEMENT

from the

NAVAL POSTGRADUATE SCHOOL
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ABSTRACT

Predicting military attrition due to conditions that existed prior to service is a complicated problem. My thesis explores underwriting practices and risk assessment in the life and health insurance industries with the aim to link private sector underwriting techniques to the military medical screening process. I review the current prediction models in the economic, actuary, and medical fields and find many of these models utilize complicated machine-learning algorithms to include random forests, deep convolutional neural networks, and deep dynamic memory neural network models. For my empirical analysis, I utilize a Cox proportional hazard model to determine risk via potential predictor variables. My findings suggest past self-inflicted injuries, substance use disorder (current and in the past), waivers for drug offenses, missing an Armed Forces Qualification Test (AFQT) score, and deployments (current and in the past) are associated with higher hazard rates of separation. This information provides insights regarding the separation risks associated with various indicators.

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LIST OF ACRONYMS AND ABBREVIATIONS

AFQT	Armed Forces Qualification Test
AUC	Area Under the Curve
CART	Classification and regression tree
CHAID	Chi-Square Automatic Interaction Detection
DCNN	Deep Convolutional Neural Networks
DEERS	Defense Enrolment and Eligibility Reporting System
DODMERB	Department of Defense Medical Examination Board
EHR	Electronic Health Records
EMR	Electronic Medical Records
EPS	Existed Prior to Service
HRs	Hazard Ratios
MAE	Mean Absolute Error
MEPS	Military Entrance Processing Station
MIB	Medical Information Bureau
ML	Machine Learning
MOS	Military Occupation Specialty
NLP	Natural Language Processing
PTSD	Post-Traumatic Stress Disorder
ROC	Receiver Operating Characteristics
RMSE	Root Mean Square Error
ROTC	Reserve Officer Training Corps
SVM	Support Vector Machine
USMEPCOM	United States Military Entrance and Processing Command
USUHS	Uniformed Services University of the Health Sciences

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EXECUTIVE SUMMARY

Predicting attrition from military service is a complicated problem. According to Marrone (2020), attrition at 36 months of service varies across branches from 18.5–29.7%. A portion of those early separations are due to non-disclosed pre-existing medical conditions. Some conditions such as mental health diagnosis are difficult to discover because of the reliance on applicant self-disclosure and remain a challenge for military medical accession screening.

To assist United States Military Entrance and Processing Command (USMEPCOM) in identifying recruits with pre-existing non-disclosed disqualifying medical conditions, my research reviews the literature on current practices in the civilian insurance industry to identify pre-existing conditions. I also review the current prediction models in the economic, actuary, and medical fields. Finally, I utilize a Cox proportional hazard model to determine the risk of separating using different predictor variables.

My key findings of the literature review are that the insurance sector utilizes various databases to serve as validated information to safeguard against adverse selection. Additionally, the actuary fields have adopted modern statistical applications to determine risk profiles of insurance applicants. Although much of the actuary models to predict risk are proprietary, other fields such as economics, medical and military manpower studies offer research with similar aims. Many of these models utilize complicated machine learning algorithms to include random forests, deep convolutional neural networks, and deep dynamic memory neural network models.

To determine a potential baseline risk profile, I use a Cox proportional hazard model on military service member data from 2001 to 2011. I estimated the hazard rates of potential predictor variables on four separation outcomes (overall and three sub categories). The results indicated past self-inflicted injuries, substance use disorder (current and in the past), waivers for drug offenses, those with missing Armed Forces Qualification Test (AFQT) scores, and deployments (current and in the past) are associated with higher hazard

rates of separation. The drug-related factors are associated with higher hazard of separation due to unfit behaviors and Existed Prior to Service–(EPS) related behaviors.

This information provides insights regarding the separation risks associated with various indicators. With further future research, I am hopeful that statistical models along with traditional medical screening methods will provide an important step in preventing early separations and accurately predicting and screening for pre-existing conditions in military applicants

References

Marrone, J. (2020). *Predicting 36-month attrition in the U.S. military: A comparison across service branches.* RAND Corporation. https://doi.org/10.7249/RR4258

ACKNOWLEDGMENTS

It is with my most upmost respect and personal gratitude to thank Dr. Yu Chu Shen and Dr. Latika Hartmann for their unwavering support, guidance, and professional insight throughout my research. The Naval Postgraduate School is blessed to have such gifted professors to share knowledge and build strong naval officers ready for the challenges in the fleet and in support thereof.

I would also like to thank all the professionals from USMEPCOM, especially Colonel Brady, Commanding Officer, USMEPCOM, who provided great insights for my research.

No acknowledgment will be complete without a heartfelt thankful acknowledgment to my dear wife and children who have persevered through many challenges with me. I could not have done anything without their support. Laudem Dei, for the many blessings.

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I. INTRODUCTION

The United States Military Entrance and Processing Command (USMEPCOM) is responsible for the efficient, effective, and timeliness of processing applicants into active duty service. Although the processes and procedures instituted at USMEPCOM are comprehensive, recruitment of first term attrition is a challenge to overcome. According to Marrone (2020), attrition at 36 months of service varies from across the branches from 18.5 to 29.7 percent. Additionally, the estimated total sunk costs attributed to attrition in the U.S. Navy ranges from $245 to $258 million. Pre-existing medical conditions are a common cause of attrition. In some circumstances, applicants can request waivers for various medical conditions disclosed upfront during the medical screening. An additional category of attrition is attributed to non-disclosed existed prior to service (EPS) conditions. Approximately 5% of new accessions, excluding the Air Force, were attrited for an EPS condition (Monahan et al., 2013). Although a portion of non-disclosed preexisting conditions are discovered through a physical medical examination, some conditions such as mental health diagnosis are difficult to discover because the medical screening requires the applicant to self-disclose medical information. To assist USMEPCOM in identifying recruits with pre-existing non-disclosed disqualifying medical conditions, my research explores a predictive mental health profile for military recruits. Specifically, I analyze the risk classification system used in actuarial science to consider best practices that may be practical to apply to the current military medical accessions. Following the trends in the private insurance sector, my research reviews automated underwriting which generated gains in efficiency, accuracy and reduced costs. The leading innovation in the insurance sector is applicable to their ability to produce accurate risk predictions for their applicants. My research aims to provide information that can lead to an accurate mental health risk prediction profile for military applicants as an informational aid for MEPS providers.

Attrition has a significant impact on the Department of Defense. According to the Defense Health Board, the current processes significantly rely on self-reporting which can lead to failure in discovering undiagnosed or unreported conditions (Poland & Parkinson, 2008). Applicants have an incentive to not disclose their information before service which prior studies suggest are responsible for 50% of separations (Poland & Parkinson, 2008).

A medical condition that existed prior to service (EPS) is defined as a condition that was verified to have existed before entering military service and resulted in a discharge within 180 days after the start of training (Monahan et al., 2013). Hoge et al. (2005) discussed the association between pre-existing or existed prior to service (EPS) mental disorders and military separations. Forty-five percent of Army soldiers who were hospitalized for the first time due to a mental health primary diagnosis left the service within six months of hospitalization. Among those who attrited due to mental health, 8% were categorized as EPS. Although this study only included Army soldiers for a single year (1998), it highlights the correlation between mental health and attrition.

To better understand the challenges that USMEPCOM faces, it is important to look at the multiple facets that are related to EPS attrition. Although not entirely inclusive, I reason that this outcome can occur due to the following reasons:

- Attrition due to non-disclosed pre-existing medical conditions unidentified during examination that would have been disqualifying and developed into a medical discharge.

- Attrition due to disclosed pre-existing medical conditions that were non-disqualifying at time of entry but developed into a medical discharge.

- Attrition due to disclosed pre-existing medical conditions that were disqualifying at entrance, but a waiver was submitted and approved for entry.

Of the previously listed reasons for EPS attrition, only the first one is outside of MEPS control. If the medical screening procedures could identify non-disclosed medical conditions at the time of enlistment, USMEPCOM would gain a greater degree of accuracy in accession screening.

RESEARCH QUESTIONS

Through my research, I will answer the following research questions:

- What is the current practice in the civilian sector to identify pre-existing conditions?
- What prediction models in economic, actuary, and medical fields would be appropriate to incorporate as a baseline risk profile as part of a practical screening tool for military entrance processing station (MEPS) providers?
- What is the mental health risk profile of active-duty recruits who attrite before their first term of completion?

Here is a summary my findings. The current practice in identifying pre-existing conditions is most significantly related to the civilian insurance industry. Accurate determination of risks and access to information that discloses risk characteristics is very important to the health of the insurance system. Applicants that conceal or are not required to reveal information are subsidized by the rest of the group. The insurance industry has traditionally determined risk of applicants through self-disclosed screening applications, medical exams, probability distribution of risk tables, actuary software computing risks as well as obtaining validated health information via various associated data exchanges that are available to the insurance industry. Today, traditional actuarial methods have evolved to adopt technology and predictive models that can offer an automated underwriting product. This new approach to underwriting has reduced both labor and time as well as increased profits and accuracy. There are multiple modern statistical methods to answer these questions. There have been numerous analytical service companies who offer products specifically for the insurance industry for the purposes of assessing risk of applicants. Although much of the actuary models to predict risk are proprietary offering little details beyond published white papers, the complete method of modeling is not revealed. Other fields such as economics, medical and military research offer research with similar aims. The economic and military attrition models tend to include logistic regression, duration analysis, as well as machine learning methods such as LASSO, random forests, and neural networks. The medical literature has detailed machine learning methods for predicting numerous medical conditions, to include a variety of mental health conditions. These models include complicated forms of machine learning such as deep neural networks that can read through a patient's electronic medical history and make a prediction for a current diagnosis as well as future diagnoses for readmissions.

In my analysis, I estimated the hazard rates of separating from the military within 6 year of service using the Cox proportional hazard model on 4 separation outcomes (overall and 3 sub categories). Using a Cox proportional hazard model on military service member data from 2001 to 2011, I estimated the hazard rates of potential predictor variables on 4 separation outcomes. The results indicated the higher hazard ratios of separation for self-inflicted injuries, substance use disorder (current and in the past), waivers for drug offenses, those with missing AFQT scores, and deployments (current and in the past). The drug related factors are associated with higher hazard of separation due to unfit behaviors and EPS related behaviors. This information provides insights and knowledge regarding the separation risks associated with various indicators.

II. INSTITUTIONAL BACKGROUND

In this section I cover the institutional background of USMEPCOM. I focus on a broad review of the medical screening process. Although the medical screening is conducted by either the Military Entrance Processing Station (MEPS) or by the Department of Defense Medical Examination Board (DODMERB), my focus will be on MEPS because they handle the enlisted recruits which is the focus population for my study.

A. USMEPCOM

Originally established in 1976, USMEPCOM is responsible for the accession of recruits across all branches. The establishment of the All-Volunteer Force in 1973, resulted in a number of accession reforms. The medical screening process was divided between USMEPCOM and the Department of Defense Medical Examination Board (DODMERB). USMEPCOM is differentiated from DODMERB in that they oversee the entire enlistment process not just medical screening. Today, USMEPCOM continues that oversight and processes hundreds of thousands of applicants (Lytell et al., 2019). In fiscal year 2018, they administered nearly 400,000 Armed Services Vocation Aptitude Battery Tests (ASVAB), over 300,000 medical examinations, and assessed over 200,000 recruits. USMEPCOM is divided into two sectors, eastern and western, which are collocated at command headquarters. There are currently 65 Military Entrance and Processing Stations (MEPS) that conduct the various procedures for military accessions. The majority of accessions are enlisted but USMEPCOM does handle a small portion of officer candidates, mainly direct commissions for certain career fields such as nurses, doctors, and lawyers (USMEPCOM, 2020).

B. DODMERB

The medical military accession process is shared between USMEPCOM and DODMERB. The DODMERB was established in 1972. Institutionally it was different from USMEPCOM in that its purpose was to establish the medical accession guidelines for the service academies. Overtime, additional programs such as Reserve Officer Training Corps (ROTC) and Uniformed Services University of the Health Sciences (USUHS) began to utilize the medical screening process offered at DODMERB. Both USMEPCOM and DODMERB have a vested interest in identifying best practices in medical screening and work collectively to identifying ways to standardize military accession screening to improve the program effectiveness (Lytell et al., 2019).

C. USMEPCOM MILITARY ACCESSION MEDICAL SCREENING.

The policy for the medical standards for military service are outlined in the DOD Instruction (DODI) 6130.03, Medical Standards for Appointment, Enlistment, or Induction Into the Military Services (USMEPCOM, 2018a). This instruction applies to all organizations within the DOD. The purpose of this policy is to have consistency in the medical standards so that it is fair and equitable for all applicants. The majority of this instruction describes the medical conditions by body systems that would disqualify an applicant for military service. By utilizing these standards, the medical screening should ensure each individual is essentially "fit for duty." Each recruit is expected to be "medically capable" to complete training and their period of contracted service (USMEPCOM, 2018a). If applicants do not meet the medical screening criteria, they can apply for service specific waivers that enable them to join the military (USMEPCOM, 2018a).

1. Medical Waiver

If the medical provider has disqualified an applicant based on the DODI 6130.03 medical fitness standards, a provider can request that the applicant be considered for a waiver. It is important to note that the MEPS providers do not have waiver authority. Instead, they can request that an applicant be considered for a waiver. Once the request is made, the designated Chief Medical Officer (CMO) of the MEPS reviews the requests and either approves or disapproves it. If approved by the CMO, the waiver is then sent to the Service Specific Medical Waiver Authority (SMWRA). The SMWRA has the definitive authority to approve or decline a waiver. However, each SMWRA relies on the documentation and clinical judgement of the MEPS providers to make their determination. Some of the factors considered in making a medical waiver recommendation are whether the condition is acute or is it chronic/progressive in nature, whether the condition will be aggravated, will the condition cause the applicant to attrite, or will the condition constitute an undue hazard to the applicant or to others (UMR 40–1).

2. Medical Screening Process Flow

Two important instructions guiding the medical screening are the DODI 6130.3 and regulation 40–1. The DOD 6130.3 lists the health standards, whereas the USMEPCOM regulation 40–1, Medical Qualification Program, determines how to conduct the medical screening. This regulation sets the procedural guidance for USMEPCOM medical qualification program utilized at MEPS locations. The general flow for medical processing is as follows: applicant check in, medical brief administered, screening forms completed, physical exams performed, qualification determinations processed, and lastly potential for waiver considerations (USMEPCOM, 2018a). Figure 1 summarizes the process.

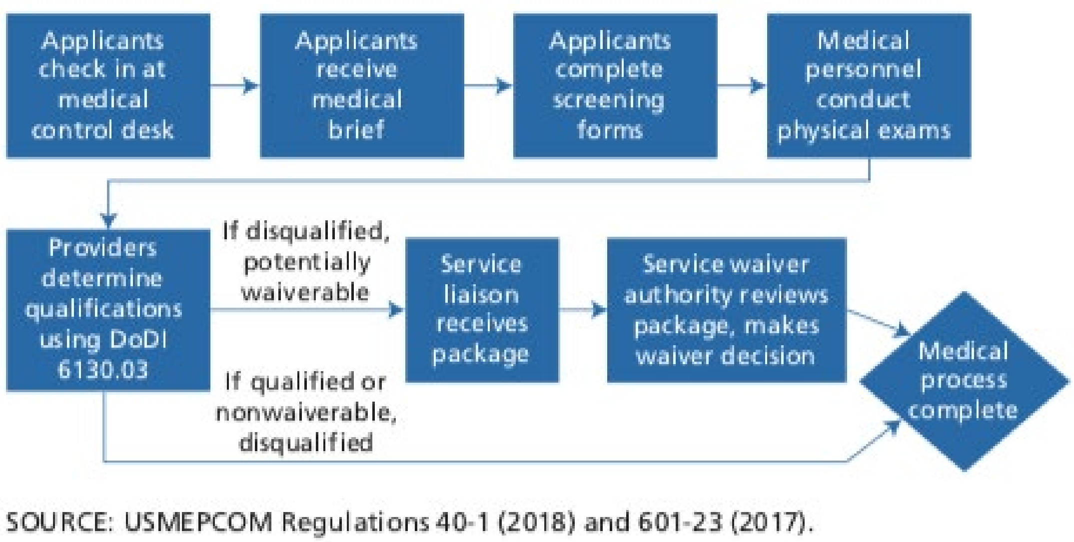

Figure 1. USMEPCOM medical screening process.
Source: Lytell et al. (2019).

3. Prescreen

The applicant medical check-in portion is done biometrically to check applicants in and out to ensure identification accuracy. The check in also serves as a review to ensure the appropriate forms are filled out and ready for review. The medical brief portion instructs and assists applicants on how to complete the prescreen required medical documentation forms. The required forms are DD Form 2005 Privacy Act Statement, DD Form 2807–1 Report of Medical History, DD Form 2808 Report of Medical Examination, UMF 40–8-1 E Drug/Alcohol and HIV Testing Acknowledgment Form, UMF 40–1-15-1-E Supplemental Health Screening Questionnaire, and the Standard Form 507 Medical Record. These forms are comparable to the screening tools used in the actuary process for private health and life insurance industries. The Report of Medical History form DD 2807 is a tool to aid physicians in the determination of the acceptability of the applicants. The information provided on the form entirely relies on self-disclosure. The DD 2807 covers a comprehensive list of medical impairments for a checklist of yes or no answers as well as a space to provide more details. A copy of form DD 2807 is viewable in the appendix.

4. Medical Physical Examination and Interview Process

The physical examination form uses DD 2808, Report of Medical Examination. Combined with the DD2807 these forms are reviewed and compared for consistency. The medical examination is a comprehensive medical physical examination conducted by a MEPS provider. The prescreen form prompts for additional screening or documentation as appropriate. While the medical examination is essential in identifying non-disclosed medical conditions that could be discovered by physical exam, it is less helpful in identifying more challenging medical disqualifiers such as mental health issues. The medical history interview is an important part of the screening process. During the interview, providers must establish a rapport with the applicant to encourage full disclosure and elaboration on the medical history prescreen form. The medical history interview must be completed before the physical examination/ortho-neuro screening (USMEPCOM, 2018b). During the interview, the provider reviews DD Form 2807–2 and DD Form 2807–1 for any discrepancies. As part of this process, the provider completes the Alcohol and Other Drug/Substance Abuse History. This portion of the history is aimed at helping the provider to determine potential behavioral/mental health conditions. The interview ascertains information via direct questions such as "have you ever used alcohol, marijuana, other illegal drugs, or other substances (such as inhalants)?" (USMEPCOM, 2018b). The provider must comment and discern appropriate condition based on the applicants answer.

The provider must determine if applicants answer is either positive or negative for a substance disorder or should be deferred due to lack of information. This can be subjective and is dependent on full disclosure by the applicant. The drug and alcohol lab screen provides a definitive identification of current drug and alcohol use but does not identify past use undetectable beyond the laboratory threshold.

Part of the behavioral health screening is conducted via reviewing the Medical History Provider Interview form (MHPI) and the Supplemental Health Screening Questionnaire. Every applicant receives a behavioral health interview where their responses to the MHPI are explored. The MEPS provider has the clinical judgement to explore or request further documentation regarding any of the applicants "yes" answers. Although the pre-screen and interview are based on self-disclosed information, part of the behavioral health screen would take into account the applicants legal history. Minor legal issues are not necessarily considered unless they became a pattern that would suggest a behavioral health issue. The results of the behavioral health provider assessment are documented in the DD Form 2907–1 and the 40–1-15-E (USMEPCOM, 2018b).

5. Physical Profile Classifier

One important part of the medical examination is the physical profile (PULHES). PULHES is a system for classifying applicants. The letters correspond to the following factors:

- P: Physical capacity or stamina.
- U: Upper extremities.
- L: Lower extremities.
- H: Hearing and ears.
- E: Eyes.
- S: Psychiatric.
- X: Air Force Incremental Lifting Device

Based on the results of the medical examination, each classifier will be assigned a numerical designator of O, 1, 3T or 3P (USMEPCOM, 2018b).

- O: open status. More information is needed to make a determination.
- 1: qualified. Medical standards are met.
- 3T: disqualified for a temporary medical condition.
- 3P: disqualified for a permanent medical condition.

Multiple numeric designators can be used for each qualifier. Multiple conditions may exist in that qualifier category. Each condition will receive its own numerical designator. This is the MEPS system in classifying applicants. It is the closest resembles to the insurance sectors risk profiling process. One large difference between the physical profiler used by MEPS and insurance profiling is that MEPS does not a calculate or assign a compiled score. Instead, each category is of the PULHES systems is like a go or no go determination vs. a combined risk score.

D. DODMERB MEDICAL SCREENING PROCESS

One key difference between USMEPCOM and DODMERB is that USMEPCOM is responsible for the entire accession process. The DODMERB is primarily focused on providing the medical examinations for mainly medical officers applicants, U.S. military service academies, ROTC, and USUHS. The DODMERB utilizes mainly contracted medical exam locations. There are approximately 400 locations in the U.S. which provide approximately 30,000 examinations each year. Many of the physicians conducting the exams at the DODMERB sites are contracted health providers (Lytell et al., 2019).

The DODMERB procedure for medical screening follows this framework: prescreening, in person medical screening, and determination. If the applicant is determined to be not qualified after the in person medical screening, the applicant makes a waiver request with the service and the DODMERB forwards the applicants package to the service waiver authority. Just as in USMEPCOM, the DODMERB does not have waiver authority. Each service has their own waiver authority to approve waiver requests.

Lytell et al. (2019), analyzed the current medical screening process conducted by both USMEPCOM and DODMERB. Perceived concerns from USMEPCOM were that DODMERB physicians were not specifically trained in "accession medicine" to meet the military needs. An additional potential concern regarded the advocacy of hometown physicians on an unqualified applicant's behalf. It is possible that a condition would be overlooked due to the rapport established. The authors argued that the DODMERB providers were not completely accustomed to USMEPCOM's procedures to identify nondisclosed health issues and therefore not as well adept. Regardless, both medical screening processes rely heavily on self-disclosure of pre-existing medical conditions.

Understanding these key differences in the medical screening process is important when considering what recruits to include in the study. My research is most interested in understanding the predictors of attrition for recruits with pre-existing medical conditions, specifically mental health conditions. Due to the dual medical screening process, I will have to carefully select and compare attrition only from MEPS sites. It is important to note that the MEPS medical screening error rate is very low, approximately only 1–2% of the attrition can be attributed to a MEPS fault. The majority of attrition due to EPS is theorized to reside with non-disclosed conditions. One of the recommendations from Lytell et al. (2019), was that there was too much reliance on self-disclosure. This was a limiting factor in their comprehensive review of the program. The study suggested to collect more biometrics on recruits and to validate self-disclosed information via other validated sources (Lytell et al., 2019).

E. USMEPCOM STRATEGIC PLAN, 2016 - 2026

The USMEPCOM strategic plan provides the Commanders intent and direction to innovate, capture opportunities and to adapt to future challenges. Ultimately, USMEPCOM is challenged to manage the sustainment of an All-Volunteer Force. One key assumption pertaining to the strategic plan is that USMEPCOM is capable and allowed to access available electronic medical, insurance, education, and criminal records and the associated databases (United States Military Entrance Processing Command, 2016). Basing off this assumption, strategic goal 1 calls for improved accuracy and flexibility in the medical screening process. Part of this goal is to improve accuracy by having providers base examinations on validated information versus relying on self-disclosures. Objective 1.3 calls for gaining access to applicants electronic medical record history (United States Military Entrance Processing Command, 2016). USMEPCOM also elaborates on the necessary ability to obtain access to reliable healthcare sources and databases. Access to these databases still require the consent of the applicant. Objective 1.5, calls for medical informatics for ease of decision making. With an informatics tool, a provider will be able to better direct their attention to identify key elements in an applicant's health history (United States Military Entrance Processing Command, 2016).

In line with their strategic objective 1.3, USMEPCOM conducted a pilot program obtaining access to validated medical history. The pilot program utilized a Prescription Medication Reviewing System (PRMRS), a nationwide prescription database often utilized by insurance companies. The data includes applicants past and current prescription history. The applicants self-disclosed information was compared to their medication history and differences reconciled. The pilot program aimed to accomplish more accuracy in medical screening, particularly in the area of non-disclosed medical conditions that would be disqualifying. Building on this idea, USMEPCOM is considering the development of an EPS medical attrition predictive model, incorporating applicant's prescription and other medical history. Private insurance companies use such predictive modeling such as those offered by Milliman Intelliscripts Irix products. These predictive models are proprietary assets, guarded by the companies offering these solutions. A review of insurance sector will gain insight on how risk profiles are created, and to what extent are these predictive models being utilized in the insurance sector.

III. REVIEW OF RISK PROFILING AND UNDERWRITING PROCESS IN THE INSURANCE INDUSTRY

It may not seem apparent at first, but USMEPCOM and the insurance sector both have a similar problem. They both need to accurately identify the risk of each applicant so they can make a decision on whether to recruit, in the case of USMEPCOM, or insure in the case of the insurance industry, that individual. The military utilizes applicant's information to evaluate for medical standards. The insurance industry utilizes applicant information to evaluate acceptable risks for insurance product pricing. Lessons can be pulled from the civilian sector, especially the health and life insurance sectors. In this Chapter I explore basic concepts from the insurance industry to better understand how the civilian insurance industry manages the risks associated with pre-existing conditions. This information is useful in determining if there are any relevant insurance practices that could enhance USMEPCOM's ability to identify high risk recruits at the time of application.

A. THE INSURANCE INDUSTRY AND RISK PROFILES

Creating accurate risk profiles is vital for the insurance sector. They must understand and accurately calculate the risks they take by accepting an applicant in its pool of insured persons. They want to accurately price the premium so that they do not end up paying out more claims than they receive in premiums. The insurer wants to determine if the applicant is of "average" health. If so, they can be charged the standard rate. If there are deviations from the average, either above or below, additional adjustments to the premium will determined. One of the most commonly used tools to assess risk in actuary science is the life tables. In the most basic form, the life table groups ages of individuals, counts the number of individuals who died or are living at each age and determines the probability of living or dying at a particular age. Other variations of life tables include other factors that account for variable risks such as medical conditions, smoking, etc. There are normally separate life tables for men and women to account for the gender differences in mortality across the ages (Kagan, 2020). The life tables are based on the law of large numbers. This is important because a sufficient sample size is needed to determine accurate probabilities of an insurable event happening and diversifying that risk across that space.

This is a key process when determining the pricing of insurance products. The risk, in terms of losses, should be reasonably predictable as well as monetarily measurable. The probability distribution of the risk should be known. One key attribute to insurance risks is that it should be random.

This concept is central to the insurance underwriters in that they must accurately predict the chances of the insured random event to obtain accurate pricing and avoid adverse selection (Gupta, 2007). The probability distribution tells all the possible outcomes and the probability of those outcomes to make an informed decision. For example, take 10 members in a life insurance group, all charged a premium of $1,000 USD. Each has the same life insurance policy issuing $100,000 USD in the case of death for a given period of time. If two persons out of the ten are likely to die, the probability for death is 20% for the group. That being said, the company would have an expected loss and would have to adjust its pricing as shown by the following. So they would need to increase their premiums by an additional $1,000 USD to cover the expected value of losses.

Total Premiums collected	=	$10,000 ($1,000 x 10)
Expected Value of Losses	=	$20,000 ($100,000 x 0.2)
Net(loss)	=	$10,000 ($20,000 - $10,000)
Premium Adjustment	=	$1,000 (total premium $2,000 per person)

By classifying each applicant by their risk, the underwriter is essentially trying to assign actuarially fair premium for each applicant. The risk profile comes into play where each applicant is assigned their probability of death. Each applicant has to be accurately "siloed" into the correct probability category in order for the premiums to cover the expected value of losses.

B. PRESENCE OF ADVERSE SELECTION IN HEALTH AND LIFE INSURANCE MARKETS

The ability for an underwriter to assign each applicant to the correct risk category is critical due to the problem of adverse selection in the health and life insurance market. In a completely voluntary world, a young healthy person would have very low desire to purchase a health insurance policy whereas a sick person who anticipates large medical expenses would have strong desire to purchase health insurance. Buyers of these insurance products typically have more information about their own health status than the insurance companies who sell those policies. Such asymmetric information between buyers and sellers lead to the problem of adverse selection in these markets. The applicants only want to purchase insurance when they have high certainty that they will use such products. The applicant has control of when to purchase, how much and of what types of products. This gives the applicant a financial advantage because they base their decision on their own known risks and ability to self-classify or self-determine their risks. All of these risks are not known to the insurer which leaves them at a disadvantage. For example, an individual who conceals being alcoholic, knows they are at risk for a slew of medical problems. Unless the applicant has a documented diagnosis, the insurer would likely not detect the health issue and adversely select that applicant. The underwriter essentially classifies the applicant as reasonable health vs. a higher risk. In turn, this applicant will use the benefits and drive the costs up for the (average health) covered group for which they are pooled. This concept is very much like a subsidy, in that the healthy individuals in the group, are the ones who pay for the unhealthy users. If adverse selection is severe for a particular insurance product, eventually the premiums will rise to a point where the majority of the healthy individuals will not be able to afford or even value the policy (Cummins et al., 1983). Understanding the risks upfront by calculating the applicants risk profile helps the underwriter make informed decisions on pricing and/or denial of coverage. In essence, the adverse selection problem facing the underwriter in the civilian sector is not that different from the problem faced by USMEPCOM—it is costly to train each recruit for the military service, and recruits who did not disclose their full medical history will drive up the personnel cost down the road due to higher than expected health care cost and/or the cost to replace them.

Accurate determination of risks and access to information that discloses risk characteristics is very important to the health of the insurance system. Applicants that conceal or are not required to reveal information are subsidized by the rest of the group. Typically, to mitigate adverse selection, the insurance company will rely on validated information from a database, a medical exam, laboratory tests, and biometrics. Medical history and databases offer validated information that aid the underwriter. Insurance companies utilize these health information databases to help discover undisclosed risks. For example, if the applicant reports not having any recent hospitalizations, but the insurance claims database reports an overnight hospitalization for asthma, the application then gets cued for further investigation. The more comprehensive databases will include demographics, administrative data, health risks, and health status information. The health status includes a medical history, current medical encounters and outcomes. Most of the information supplied to these databases is via health insurance claims. If an individual does not have health insurance or seeks medical care out of their state of residence, they may be missing from these databases. In order for individual risk profiles to be conducted, these databases must use unique personal identifiers to link the health information to an applicant. Typically, these will be an applicant's social security number or some unique alpha numeric code. These identifiers may not be used by specific hospitals or providers thus making linking multiple databases difficult for a longitudinal study. There are specific health database organizations (HDO) who control, maintain, and release data for various uses. They acquire their information from various sources and sometimes use a network of databases to compile aggregated information. Some of the data bases accessed are various State mandated hospital discharge databases as well as other state, federal, and private data repositories (Donaldson & Lohr, 1994). One example of a state-aligned privately managed HDO is the Health Data Consortium. They are a nonprofit corporation, chartered by the commonwealth of Massachusetts, they aim to provide efficiency's in health care that improve the quality of care by offering health data analysis services (Massachusetts Health Data Consortium, 2020).

Another commonly utilized database is the Medical Information Bureau (MIB). The MIB was established in 1902 as non-profit members-only organization. For their members, they offer underwriting services for health and life insurance products by analyzing individuals risks (MIB, 2020). Mainly, they offer a source of validated information to check against the applicants self-disclosed information. The MIB offers a means to guard against adverse selection due to an applicant's non-disclosed information.

Any misrepresentations and omissions in the application would alert the underwriter and mitigate possible inaccurate risks assessments. The MIB utilizes information from its members existing insurance policies and is sometimes commonly referred to as the "Information Exchange." Each member has access to the database but in order to utilize the data, they must have the consent of the applicant. The MIB Underwriting Services Consumer File is accessible to consumers to review their own documented information if they have an existing file. The MIB receives information that is included in its underwriting life and health insurance membership information exchange. The MIB manages and controls its own database. The MIB uses proprietary codes so that it does not store, collect or maintain comprehensive medical records. These codes offer brief summaries to act as alerts to a medical impairment or risk pertaining to morbidity or mortality. Members are prohibited from making determinations solely based on these codes due to the fact that they are very general. The purpose is to allow the underwriter to investigate further and gather additional information for risk determination. The MIB information is only stored for a period of seven years before it is removed (MIB, 2020). Through its various data bases, the MIB also offers identity verification, criminal history, and a motor vehicle report. Verisk, otherwise known as Insurance Service Office (ISO), offers a wide variety of claims information via its databases. Additionally, they provide ancillary services statistical, actuary, underwriting, fraud detection, technical services and claims information. Additional database such as consumer credit data, consumer prescription drug data, department of motor vehicle data, as well as licensure records are currently being utilized to develop automated underwriting solutions that provide applicant risk predictions.

According to English and Lewis (2016), the privacy protection of insurance product applicants is important and each state may have different regulations on guarding privacy. The legal requirements vary by state and federal laws. Those laws and regulations will have implications for insurance reportability and the claims process. These laws are to ensure the confidentiality of patient's health information which we commonly refer to as the federal Health Insurance Portability and Accountability Act (HIPAA) rules and covers protected health information (PHI) (English & Lewis, 2016). Under HIPAA, adult patients and minors who consented to care can request restrictions on sharing their PHI. If the individual's health care has been fully paid for and does not involve insurance or any health plan coverage, with the providers agreement, restrictions on reporting can be allowed. Additionally, health plans must accommodate reasonable requests for restrictions but the patient may have to demonstrate an endangerment resulting from the disclosure of their health information to the data exchanges (English & Lewis, 2016). In some states, provisions in the law allow and at times require disclosure of confidential health information. Some of the more sensitive areas are in the mental health, sexual reproductive health, substance abuse treatment, and minors involved in domestic violence/abuse. When patients consent to treatment, HIPAA allows for the sharing of PHI for health insurance claims for payment. In addition, PHI may be used for treatment and for aid in healthcare operations (English & Lewis, 2016).

C. THE TRADITIONAL UNDERWRITING PROCESS

When an insurance company sets out to write a policy, they typically are aiming to accomplish three objectives. The first is to make sure they conduct their evaluation in a fair and equitable process. Secondly, the product pricing must be competitively priced but also cover the costs of assuming all of the calculated risks. To be a viable business, the premiums must be priced accurately to account for and cover all the business expenses to include the payout of coverages (Gupta, 2007).

In the case of life insurance, the underwriting process begins with receiving the applications and other information. Life insurance is unique in that the probability of death must be determined prior to the start of coverage and remains effective through the term of the policy. Some policies cover an individual for more than 30 years. The risk of death is calculated at the plans inception and is not adjusted intra term. Therefore, it is extremely important for companies to make accurate predictions about an applicant's probability of death. The predictions are based on a collection of information. They typically combine demographic, medical, lifestyle, and occupational information to get a collective prediction of mortality. Similar to the screening questionnaire administered by MEPCOM to new recruits, the general information is usually obtained by a questionnaire which rely on self-disclosure. The medical information is more extensive and often involves a medical exam for which both self-disclosed and observable medical characteristics are determined. The underwriter will review the information and based on the information gathered, may request additional information to help them accurately determine the risks. These risks are then used to classify the applicant into a class of varying risks. Typical classes are: preferred class, standard, and sub-standard. The preferred class has a less than average risk for mortality. The standard class is the average risk and the sub-standard class has a higher than average risk of mortality. If the applicant carries too much risk and will not fit the into either of the risk classes, then they would be denied coverage. Risk classifications help determine what characteristics show a relationship to added costs. Developing these classifications usually follow the principles and standards of underwriting profession. Often these classification are updated as health care expands treatments to increase longevity (Cummins et al., 1983).

1. Factors Generally Considered by Life Insurance Companies

According to the American Academy of Actuaries, the two biggest factors that affect life expectancy are age and gender. For many years age was the largest factor considered for mortality. Overtime, gender and tobacco use became significant in classifying applicants. Medical conditions also remain a significant factor in determining risks. The underwriter has to classify each disclosed condition into one collective single measure of additional mortality. The combination all mortality is allocated an overall level of risk. The standard risk category is the benchmark group and is assigned 100% of the expected mortality. Various factors such as height and weight characteristics, medical conditions, occupation and lifestyle that deviate from the benchmark are assigned a percentage to either credit or debit its rating. This is commonly referred to as the numerical rating scale. Once a final numerical rating scale is calculated, it represents the percent deviation from the benchmark. For example, if an individual's numerical rating is 145 percent, then their expected mortality is 45% higher than the standard person. Suppose a person has diabetes, and the correlation of diabetes to death was determined to be 2.0 times that of the standard risk group, then they would have a 100% debt and assign a rating 200 percent. Taking this concept further, let us say this same applicant reported no family history of heart disease, which is determined to relate to a lower chance of mortality by .10

times of the standard group. This would then credit the rating 10 percent. Therefore, the rating would be lowered from 200% to 190%. In the end, if these were the only two factors considered, the combined rating for this applicant would be 190% of the standard group (Cummins et al., 1983). To get the final numerical rating, all of the calculated deviations from the benchmark are summed into a final numerical rating.

Insurance companies have set ranges of what they will accept at the standard rate. Some insurance companies are flexible on how they set the acceptance of standard rate. Some insurance reject applicants if the risk is above predetermined threshold. The others have an adjusted premium based on the substandard numerical rating. The majority of applicants, approximately 90% of the population fall in the standard rates (Cummins et al., 1983).

2. Non-medical Factors

Insurance companies have a set of relatively standard non-medical factors that are ascertained in applications. Typically, these factors are: the type and amount of the insurance product requested, how much insurance coverage requested, address, date of birth, sex, marital status, current occupation, annual income, and the designated beneficiary. Additional factors asked that correlate with mortality are questions about auto accidents, revoked or suspended license, and speeding tickets. Other factors considered relate to leisure activities. Some applications ask if applicants participate in recreational risky sports like auto/marine racing, scuba diving, hang gliding etc. Occupation questions such as identifying if there was a recent change in occupation helps deter adverse selection. For instance, if an applicant was previously employed in a high risk occupation with long term consequences, this information would be omitted and the applicant would be classified according to their current lower risk occupation. Other non-medical questions are foreign travel and military status. Another important question asked is if the applicant has ever applied for insurance in the past, been denied, or received less coverage than was asked for. It is important to point out, that all these questions are self-disclosed by the applicant and relies on the integrity of the applicant (Cummins et al., 1983)

3. Medical Factors

Some of the standard medical information asked by the insurance company are height, weight, family history, recent doctor's visits, surgeries, and health impairments. Typical questions asked by the majority of insurance agencies according to Cummins et al. are: Has the applicant ever had or been advised to receive a clinical treatment or diagnostic test within the last five years? Is the applicant taking prescribed medication and/or under the care of a physician for any medical condition (Cummins et al., 1983).

Other sensitive factors include information regarding abnormal pregnancies, menstrual abnormalities, and reproductive factors. Additionally, some insurance companies ask if they are any form of disability or have been discharged from the military due to a mental health or behavioral issue.

Some medical impairments carry additional risks when they are combined with other impairments. For this reason, additional combination ratings are listed to give a more accurate estimate on mortality. For instance, high blood pressure combined with an enlarged heart would have a different rating than adding the two separate factor ratings together. The list of medical impairments and factor adjustments is extensive and differs by insurance companies. In some cases they are regulated by state laws and restrictions.

4. Application Forms

Insurance companies gather information in a variety of ways. One of the more straightforward processes is the application form. Individuals fill out various standardized forms early in the application process. Forms vary from company to company but are uniformly aimed at gathering information in a short succinct way in order to determine the nature of risk associated with the applicant. As discussed above, generally applicant information ascertained from the forms are administrative, demographic, non-medical, and medical factors. Most often these forms are now offered online electronically or are built into the insurance companies' software that is incorporated into a secure website for automated underwriting. One important point to note, is that most applications have an authorization clause with a signature block. This authorization block provides the legal language and is the legal authorization for underwriters to ascertain applicant's data from the various databases discussed earlier.

5. Medical History Information Requirements

The medical history information requirements vary and are dependent on company policy. According to the Cincinnati Life Insurance Company's underwriting handbook, the use of tiers for medical requirements based on the applicants age and requested amount of insurance. Typically, as the applicants' age increases, the requirements increase. As the applicant's insurance amount increases, so does the information requirements. Based on these principles, the older applicants with higher coverages require the most medical detail (The Cincinnati Life Insurance Company, 2017).

D. INNOVATION IN UNDERWRITING METHODS

The insurance industry has adopted more modern statistical analytics processes to determine risk and to price policies. Traditional actuarial methods, as I described earlier in this chapter have evolved to adopt technology and predictive models that can offer an automated underwriting product. This new approach to underwriting has reduced the laborious time for an actuary to make a decision on an applicant. Through statistical modeling, more accurate predictions open up the opportunity to approve more applicants that would have been otherwise declined. In this section, I briefly discus these modern methods of predictive analytic services.

1. Automated Underwriting

Prior to automated underwriting, the traditional underwriting process required physical paper and hand completed forms. These forms then had to be scanned into electronic data warehouses. Once the information was located in the warehouse, then underwriters could access these scanned documents online (Aggour & Cheetham, 2005). Since then, there has been a revolution leading to the development of automated underwriting. Automated underwriting can have different meanings. Aggour et al. refer to it as using artificial intelligence to automate the underwriting process (Aggour & Cheetham, 2005). Okeefe (2013), uses automated underwriting and "e-underwriting" interchangeably. Batty et al. (2010) defines automated underwriting as "a technology solution which is designed to perform all or some of the screening functions traditionally completed by underwrites, and thus seeks to reduce the manpower, time, and/or data necessary to underwrite a life insurance application" (Batty et al., 2010). Automated underwriting essentially digitizes and streamlines the underwriters process making it more efficient and productive. Okeefe (2013) argues the benefits of automated underwriting drives growth, better utilizes resources, delivers better customer service, and has significant payback potential. In 2010, the Society of Actuaries (SOA) found that many insurance companies desired to improve the efficiency of underwriting and there was strong interest to move into automated underwriting. However, only a small portion of companies were actively adopting it (Batty et al., 2010). Insurance companies were using automated underwriting in many different ways and had different levels of success with it. Not all the companies utilizing automated underwriting had the same capabilities. By 2010, 54% of the firms had the capability to reach a final decision and recommend a underwriting decision. On average, 41% of the firms could reach a underwriting decision without the review of a underwriter (Batty et al., 2010).

Among the satisfied companies utilizing automated underwriting, the cost savings ranged from 20–80 percent. The main cost reduction was related to time. Automation also generated more sales. A 2019 Insurance Barometer Study found that 9 in10 companies are in the planning stages or have already began developing automated underwriting programs (Lorillo & Leyes, 2019). The insureres were satisfied with the risk selection genereated by automated underwriting at that time, because they were using identified risk in the same underlying methodology as non-automated systems, so the risk selection is consistent across both platforms (Batty et al., 2010). That howerver would change as the most current automated underwriting however shifts from the traditional methods to multivariate analysis and predictive analytics. The current capabilities of automated underwriting have evolved considerably from the initial rules based models. For instance, in an older rules based model, an individual would be given points or debits for health risks that would collectivly add up to produce a score. The technology was a digital version of the old underwriting methodology. Currently, the technology and data uses multivariate analysis.

This is different because all of the rating variables are subject to correlation and the interdependecy of variables produces a more accurate prediction compared to the traditional look up tables (Bosco, 2020). There are numerous companies offering multivariate analysis for risk predictions. Unfortunelty, I have not been able to find any details about these models due to the fact that they are propreitery and guarded. Although many of private sector acturary analytic businesses offer white papers discussing the effectiveness of their products, mainly as a selling tool, they do not give any detail regarding their methodology. Regardless, there is usefull information that these companies offer about their products from their white papers, brocheures, and websites. From the surge of these analytic services and products, it is clear that the future of underwriting is heavily reliant on multivariate analysis.

2. Examples of Current Private Sector Actuary Analytic Services

Perhaps one of the worlds larges providers of actuary products and services in the private sector is Milliman Inc. IntelliScript, which offers risk management solutions. Irix, a proprietary statistical modeling product, interprets in real time, data to assess applicants risk. Prescription, Medical Information Bureau, credit, medical, Motor Vehicle Record, and application data are utilized to interpret a risk score for underwriting purposes. There are little to no studies available describing the methodology of Irix model due to confidentiality of the propriety software. In 2019, Munich American Reassurance Company published a white paper evaluating the Irix risk score with credit data. Key findings of the reports were: the combined score which included credit data along with prescription history was positivly correlated with relative mortality risk. The combined score identified more lives with low mortality compared to prescription only risk score. The combined score correctly stratified mortality risk across age groups (Li, 2020). The following is a list of the types of credit information utilized by Irix: inquiries, number of accounts, types of accounts, oustanding balances, derogatory marks, payment history, credit limits, collections, foreclosures, and bankruptcies (Beaulieu et al., 2019). The prescription data utilizes a variation of the following information: prescription brand/generic name, dosage, date of fill, prescribing physician, pharmacy, dates of eligibiity, underwriting significance indicator by color (Carlson, 2018). Additionally, other rules variables are: indication/therapeutic class, drug combinations, fill timing, physician specialty, gender/age, diagnosis/procedure combinations, and drug/diagnosis combinations (Carlson, 2018). Although these are likley to be incorporated as independent variables in the model, due to not having the methodology, its not clear of what type of statistical model is being used to drive the prediction. Due to the shear volume of data and possible non-linear relationships of the data, I imagine that the Irix model uses some form of machine learning such as an esemble model that combines multiple prediction models, parametric and non-parametric in one single prediction or applicant risk rating.

Verisk Analytics also offers data analytics services to the insurance sector, energy markets as well as the finacial sector. The Verisk Medical Black Box product automates the medical risk assessment process and provides a breakdown of the different risk exposures in healthcare. Verisk also offers four models designed specifcially to detect fraud and non-disclosure for the life insurance industry. One such model is know as the Avocation Model. The Avocation Model utilizes artificial intelligence and machine learning specifically designed to discover non-disclosed risk hobbies and avocations. According to Verisk, 14% of individuals engage in at least one risky hobby (Livada, 2020). The proprietary Avocation Model pulls marketing and licensing data to identify high risk hobbies thereby assigning a letter grade score for applicants. Verisk claims the model identifies the following high risk hobbies: aviation, ATV, boating, hunting and fishing, motorcycle riding, motocross, scuba, snowmobiling, and various extreme sports (Livada, 2020). Additionally, the Verisk developed the Tobacco Usage Propensity model. This model was designed to discover "lying smokers" from non-disclosure of smoking status through the use of audio analytics. The model measures dysphonia markers which are impairments or degradations to a persons voice due to the damage of irritates commonly associated with tobacco products (Zilwa et al., 2020). The detection is divided in three stages with respective sub-stages that ultimatley returns a probability score along with a confidence interval. In the white paper report, through the initial training data, the model could correclty identify smokers 85% of the time (Zilwa et al., 2020).

Although there are private analytics companies offering automated underwriting solutions, the problem of discovering fraudulent claims at the time of application is a complex issue. The Affordable Care Act (ACA) protects individuals against private insurance companies' discrimination against pre-existing conditions. An individual cannot be denied or refused coverage on the grounds of having pre-existing conditions. They also cannot be charged more because they have a "pre-existing condition." ACA also states that the benefits cannot be limited for pre-existing conditions. The ACA does not protect individuals in the case of fraud, grandfathered policies or short-term policies (Patient Protection and Affordable Care Act Health Related Portions of the Health Care and Education Reconciliationact of 2010, 2010). Non-disclosure of adverse health information would be classified as fraud. Although discovering non-disclosed pre-existing conditions is a problem for the health insurance industry, it is not entirely clear how big of a problem it actually is. There is likely no incentive for an individual to hide, mis-represent, or non-disclose a health condition that would lead to fraud and ultimately deny them coverage. The insurance industry utilizes application forms, medical exams, diagnostics, and various medical records to gather information on each new insurance applicant. Through a combination of these sources, the risk is determined for each applicant and a decision is made. Scholarly research is deficient on the topic of discovering or uncovering a predictive profile for applicants that purposefully conceal medical information to obtain health insurance. Through the use of the various medical databases such as the MIB, underwriters are able to identify pre-existing conditions by reviewing the applicant's medical history. In the case that something was missed by the underwriter or the applicant intentionally misrepresented in the application, a significant claim would trigger and after-action review of the application. During that review, the underwriter would carefully conduct a thorough review of the patient's medical history through all available sources. Insurance companies, biding by the state laws and the terms of the contract, may have the right to rescind the policy. Schumann discusses in his article an example of an individual who failed to report that his physician recommended an ultrasound of his liver as a follow up to abnormal liver function labs. The applicant reported "no disease or disorder" of his liver. The applicant died a month later and the review of his application lead to a rescinding of his policy that was upheld in court (Schuman, 2015). Most state laws allow the insurance policy to include a clearly stated void in contract due to a misstatement by the insured (Schuman, 2015).

Through a recission of policy, the insurance industry has a means to recover the damages that occur from intentional misrepresented applicants withdrawing the need to predict these types of applicants. The insurance industry is starkly different from USMEPCOM in that misrepresentations that lead to EPS attrition are not recovered and are lost resources. The ability to contractually and legally "rescind" or recoup expenses from recruits is currently not part of the organizations plans.

E. IMPLICATIONS FOR USMEPCOM

What does this mean for USMEPCOM? Traditional methods such as probability distributions, can be useful for identifying the probability and trends from accession data. Essentially, USMEPCOM would like to determine the probability that they would randomly select an applicant who was hiding a medical condition. However, this question would likely never be answered because we never truly know or can identify the event "hiding a medical condition." What could be determined from the data could be "what portion of EPS attrition is due to a non-disclosed medical condition." This is getting closer to answering the question but we would still need to have an accurate and consistent system in cataloguing and determining if the condition actually existed prior to service. Since not all non-disclosed medical conditions would be captured, only those conditions that led to attrition would be identified. Elaborating on this concept, probability is explained as the chances of an event occurring given a complete set of total occurrences. As in our question above, we would never actually know the set of total occurrences. If we sampled any given MEPS on a particular day, out of the total number of applicants medically screened, how many of those screened concealed a medical condition? If we could accurately determine that answer, we would have one sample. Repeating this process multiple times, across all MEPS would increase the sample size and create our probability distribution. The traditional methods used by the insurance industry are more useful for determining the probabilities of an applicant to have a certain medical issue vs. trying to determine the probability that an applicant will hide medical information.

The screening processes of the insurance industry and MEPS are similar in that they both require self-disclosure. The medical forms are similar and capture the most pertinent information. Every military applicant is subject to a detailed physical medical exam whereas the insurance industry is more selective with medical exam requirements. The insurance company does not have the same physical requirements as military service and can save on those expenses. Determining if an applicant is medically qualified for military service is essentially like the insurance industry only offering their products for their healthiest top tier. For this reason, the comprehensive medical screening by MEPS is not likely to be replaced by an analytical model. Instead, an analytical model may provide valuable information to be used in conjunction with the existing process. The insurance industry has the advantage to utilize validated information from various databases. Essentially, by running a query through these databases, underwriters can see whether any insurance claims have been used for this applicant and validate the self-disclosed information. Gaining access to these forms of validated information is an important first step for MEPS providers. This coincides with the strategic goals for USMEPCOM and efforts to gain access to databases such as the MIB, prescription medication databases, and electronic health records. Access to validated data will be important to safeguard against EPS conditions.

Both the life insurance industry and USMEPCOM have to determine risk upfront. However, the outcomes of interest are very different. The life insurance industry is interested in the probability of death, while USMEPCOM is interested in the probability of medical EPS attrition. The processes that are specific towards risk profiling for the life insurance industry will not directly translate into a USMEPCOM solution. However, specific strategies utilized by the insurance industry can be tailored to fit into a EPS probability solution. For example, insurance industry utilizes analytic models to cut back on lengthy and expensive traditional methods. Also, through more sophisticated multivariate modeling methods like those already used in automatic underwriting services in the private sector, the accuracy of risk profiling has improved over traditional methods. Automated underwriting has revolutionized the private insurance sector. Private sector analytic services are available to support the insurance industry. These same approaches could potentially be utilized by USMEPCOM. My research is a modest step in developing such an analytical tool in the context of MEPS. My next chapter will devote to a review of recent development in multivariate models, in particular machine learning techniques that would be suitable in the context of USMEPCOM.

IV. LITERATURE REVIEW ON PREDICTION MODELS RELATED TO MENTAL HEALTH

Mental health conditions are some of the most difficult medical conditions for USMEPCOM to screen for because they rely on self-disclosure. There is extensive research on mental health in the U.S. Military. Riddle et al., studied a millennium cohort to determine the baseline prevalence rate of common mental illnesses and found it to be comparable to the civilian population. In this study, alcohol abuse, at 11.9%, was the most prevalent mental health disorder. The United States prevalence rate of common mental illness is estimated to be at 26%, which is the highest out of the Americas, Europe, Middle East, and Asia (Riddle et al., 2007). Screening for psychological disorders in the military makes intuitive sense but is very difficult and come with challenges. Jones et al. (2003), through a comprehensive literature review, found that psychological screening programs often fail and sometimes have a negative effect on recruitment goals. Additionally, there has been no identified instrument to accurately assess a recruit's psychological vulnerability. Screening for mental health remains a challenge for MEPS providers. In my literature review, I explore how mental health behaviors are predictors for various military outcomes. Then I explore the literature and methodology related to predicting those mental health related behaviors. Lastly, I review other machine learning models used in military analysis, mainly to predict separation. These models tend to relate more to the economics literature and will provide a well-balanced perspective on predicting military separation. By including both medical and economic literature, I intend to provide a more comprehensive analysis relating to predicting EPS attrition of military applicants especially related to mental health conditions.

A. MENTAL HEALTH AS A PREDICTOR FOR VARIOUS OUTCOMES

Mental health conditions and behavioral disorders have a meaningful impact on numerous military outcomes. Hoge et al., researched service members hospitalizations and their relationship to service separations. The study found that 45% of soldiers that were hospitalized for the first time for a primary mental health condition, left the military service within six months of their hospitalization (Hoge et al., 2005). Shen et al., researched the associations of suicide with deployments. The study reported that suicide within the U.S. military had increased since recent wars, which accounts for 20% of all deaths (Shen et al., 2016). The study provided insight on the risk factors for military suicides. The sample population included all uniformed service members from 2001–2011. The hazard rate of death by suicide was lower for those during deployment compared to those that never deployed (HR=0.5; CI, 0.4-0.61). However, after a deployment, the hazard rate was found to be significantly higher (HR=1.51, CI, 1.17-1.96) and remained raised for 16 quarters post deployment. Interestingly, waivers for mild mental health conditions that have resolved were not associated with an increased risk of suicide. The strongest predictors of suicide were diagnoses of self-inflicted injury (HR=8.34 vs. those with no history), and current and past mental health diagnoses (except for PTSD) (Shen et al., 2016).

The Military Health System reported absolute and relative morbidity burdens of various illnesses and injuries for the entire active-duty force. Over 16% of all medical encounters and over 48% of all hospital bed days were attributed to mental health disorders (Armed Services Health and Surveillance Board, 2019). Gunderson & Hourani (2003), studied the epidemiology of personality disorders in the U.S. Navy. At the time of the study, personality disorders were the leading cause of attrition. Shipboard men versus women were two to three times more likely to have an initial hospitalization for a personality disorder. Interestingly, submariners were found to have the lowest risk of a hospitalization for a personality disorder. Perhaps this was due to the rigorous screening for submarine duty. The analysis shown an increased risk for lower (E1-E3) paygrades. Over one half of the personality disorders were hospitalized within the first year of service. More than 50% of the personality disorders discovered were determined to have the condition prior to enlistment (Gunderson & Hourani, 2003). Similarly, Hoge et al. (2005), used hospitalization data and military separation codes to analyze mental health disorders among soldiers. The cohort was composed of active duty U.S. Army soldiers hospitalized in the year 1998. Of the 1,763 soldiers hospitalized, 40% were diagnosed with adjustment disorder followed by alcohol/drug/substance abuse (22%). Mood/anxiety, personality disorder, and psychotic disorders were significantly lower at 4%, 3%, and 4%, respectively (Hoge et al., 2005).

Cunha et al. (2015), explored the psychological attributes of U.S. Army recruits at enlistment and the relationship to attrition. The underlying premise is that individuals who demonstrate abnormal psychological health may be unfit for high stress occupations and will likely quit or be involuntarily removed. They utilized the Global Assessment Tool (GAT), which is self-administered online. It is composed of 105 questions that identifies fourteen psychosocial attributes. From these assessments, they estimated logistic models predicting the probability of attrition for the lowest five percentiles of each of the fourteen attributes (Cunha et al., 2015). The largest predictors of attrition were found to be the attributes of depression, positive affect and adaptability. The attributes that had the least effect were family satisfaction and spirituality.

From my research, in the military context, I have been able to demonstrate that various aspects of mental health are predictors of negative outcomes such as attrition. To mitigate the impacts of mental health on the military, we need to be able to improve screening by predicting if a recruit has or will develop these conditions. Next, I explore the literature on what statistical models have been developed to predict various mental health behaviors.

B. MENTAL HEALTH–RELATED BEHAVIOR PREDICTION MODELS

Military attrition due to mental health conditions remains a significant problem. In this section, I cover relevant literature focused on linear probability models as well as machine learning algorithms to predict the mental health behaviors. I focus on prediction models for suicide and depression. These mental health behaviors are closely linked to the behavioral health conditions that affect military attrition.

Gubata et al. (2012), utilized a non-cognitive temperament test called Assessment of Individual Motivation (AIM) to predict attrition due to mental health conditions. In their research, they discovered that AIM utilized during the recruitment phase offers potential for improved mental health screening (Gubata et al., 2012). AIM is a self-reported personality assessment developed by the U.S. Army Research Institute for Behavioral and Social Sciences (ARI). Essentially it ascertains information about past experiences and behaviors to identify applicants who may not be well suited for military service. The study included 47, 979 Army active-duty accessions who completed the AIM prior to enlistment. They divided the individuals into quintiles based on their composite AIM score. The mental disorders were divided into nine categories: affective disorders, psychoses, anxiety disorders, personality disorders, adjustment disorder, substance use disorders, and nonpsychotic conditions. They utilized a multivariate logistic regression for attrition and morbidity outcomes. The results showed that the lowest quintile of the composite AIM score had the highest number of individuals with a mental health disorders (45%) compared to the 5th quintile (34.5%). After adjusting for age, sex, race BMI, AFQT score, medical disqualification, and medical waiver, the lowest quintile had 44% greater odds of having a mental disorder than those in the 5th quintile (Gubata et al., 2012). The individuals in the lowest quintile were 1.6 times more likely to have an affective, adjustment, and personality disorder than those in the fifth quintile. Their study showed an increased linear trend, indicating that with higher AIM scores, the risk for mental health disorders decreases. One limitation of this study is that is only includes Army soldiers and AIM is designed for non-high school graduate enlistees. The authors recommend to replicate the findings across other branches for further validation (Gubata et al., 2012).

Stansfeld et al. (1999) similarly utilized multivariate logistic regression to predict psychiatric disorders from work characteristics and a general health questionnaire (GHQ). Their study included an eight year longitudinal cohort of civil servants who completed the GHQ at three separate phases which were: Initial phase for a baseline, follow up for phase two, and final follow up at phase three. The work characteristics measured were defined as decision latitude, job demands, and social support at work. The psychiatric disorders were defined by a score of five or greater in the GHQ and verified with a clinical interview. After adjusting for age, employment grade, and baseline GHQ score, the odds of having a psychiatric disorder where higher for those employees who had low decision authority (OR 1.29, men, OR 1.37 women) compared to those who had high decision authority. Also, employees with high job demands had higher odds of a psychiatric disorder vs. those who had low job demands (OR 1.33 men, OR 1.24 women) (Stansfeld et al., 1999). Low decision authority and high job demand often epitomizes most career fields as lower ranking enlisted member in the U.S. Military. That being sad, some career tracks offer different avenues for autonomy. It would be interesting to compare the study sample in the military context where motivation to serve and sense of duty may impact the results. Both Stansfeld and Gubata utilized separate questionnaires (GHQ vs. AIM), with multivariate logistic regression analysis, both linking them to mental health conditions. Utilizing similar questionnaires for the context of military medical screening at MEPS seems like a reasonable future aim of study.

Pham et al. (2017) utilized deep learning to predict healthcare trajectories from patients' electronic medical records. They developed a machine learning model called DeepCare which is a neural network model that is trained to read medical records and make predictions on current diagnosis as well as future medical diagnoses. A detailed explanation of deep neural networks is beyond the scope of my research. A brief explanation of the DeepCare model is that it is a deep dynamic memory neural network that is built on Long Short Term Memory (LTSM). It basically is a recurrent neural network with memory cells. A recurrent neural network uses sequences of data to predict a single output. This type of model is important because when reading the patient chart, the model is able to take past documented clinical information and to make projections on future illness. For example, past encounters, although not in sequence, are used to improve predictions for future diagnosis much like the analysis done by a human reading a patients charts. It also takes into account the episodic nature of patient encounters (Pham et al., 2017). The researchers utilized a mental health sample of 6109 patients with 52,049 admission records. The model was tested on predicting diagnosis, intervention recommendation, and future risk of unplanned readmission. The performance of the model was measured by percentage of accuracy of each type of scenario. The DeepCare model outperformed Markov and plain RNN models in all scenarios. In the first time step, Markov models accurately predicted 9.5% of the time while plain RNN was 50.7% and DeepCare at 52.7% (Pham et al., 2017).

In the context of USMEPCOM, using applicants' medical records and deep learning algorithms similar to DeepCare would be useful in identifying applicants who may be at risk for hospital readmission and map a trajectory for future illnesses. However, what is unknown is how the model would perform without an explicit mental health diagnosis or medical history. It is somewhat less useful because the applicants with these documented medical histories would likely not be candidates for military service in the first place. In the next sections, I overview models that are aimed at predicting specific mental health behaviors which may be more useful in the medical screening context.

1. Suicide Prediction

Su et al. (2020), utilized electronic health records and machine learning to predict suicide risk for children and adolescents. Different from Pham et al. (2016), the electronic health records utilized in their study were already in readable database form vs. scanning raw clinical text. The database included 129,485 patients ages 10–18 with 641,708 visits from 2011–2016 (Su et al., 2020). The outcome of suicide was divided into different prediction windows ranging from 0 to 365 days. They included a broad list of variables as potential predictors such as demographics, prescribed medications, diagnosis codes, and laboratory test. They randomly separated a training set of 90% observations and a 10% test set, then applied a sequential forward selection classifier, logistic regression and fivefold cross validation (Su et al., 2020). Across all prediction windows, the models predicted suicide behavior with an overall area under the curve (AUC) greater than 0.80. The AUC refers to the receiver operating characteristics (ROC) curve which represents the overall performance of a classifier (James et al., 2013). The AUC takes on a value of from 0 to 1 and if the model performs equally to chance, the AUC will be 0.5. The closer the AUC is to 1, the more accurate it is. For all windows, the model was able to accurately predict 53–62% of the suicide cases and has a 90% specificity rate (correctly identify those without suicide cases) (Su et al., 2020).

Coopersmith et al. (2018), utilized deep learning to analyze user's social media posts to predict suicide risk. Tradition suicide screening has significant challenges. One is that the timing of screening is important. The time between the onset of symptoms and a suicide attempt can be very short. Another is that detection usually requires self-disclosure. Only 24.6% of patients that attempted suicide visited a health care professional within one week time of their attempt (Coppersmith et al., 2018). The researchers turn to social media data to make a suicide risk prediction model. They combined two public data sets containing public information from social media. Essentially, the researchers take a phrase of text from a social media posts and train a deep learning neural network classification model to predict a suicide risk. The aggregated scores from multiple posts then collectively predicts a single users suicide risk. The models performance was evaluated via ROC curves. From the ROC curves, at a 10% false alarm rate, the models ranged from 70–85% true positive rates, which the researcher claims to be state of the art performance on suicide risk prediction (Coppersmith et al., 2018).

2. Depression Prediction

Geraci et al. (2017), applied deep neural networks to predict youth depression from unstructured texts derived from electronic medical records (EMR). Their research was aimed at identifying research candidates for by using natural language processing (NLP) and machine learning (ML) to identify youth patients with depression (Geraci et al., 2017). Patients EMRs do not always include structured diagnosis codes, which makes it difficult to screen for research inclusion criteria. Their aim was to build a model that could use NLP and ML to identify patients age 12–18 with a DSM-IV diagnosis of Major Depressive Disorder while excluding other DSM-IV diagnosis. Two methods were utilized, brute force and feed forward deep neural network. The brute force method scanned for keywords that lead to an accept or reject of particular documents in patient chart. A positive dictionary of words was selected for inclusion and a negative dictionary of work were used for deselection of words. In addition, the surroundings words were scanned to allow for context. The neural networks method worked by encoding information to make a prediction from multiple layers of information on frequencies of words used. The brute force method performed poorly when cross-validated with an approximate 50% sensitivity and specificity, meaning it was no better than flipping a coin. However, via training two feed forward deep neural networks, a combined ML model had a specificity of 87% and sensitivity of 75% (Geraci et al., 2017). Utilizing ML with NLP can provide a means for USMEPCOM to gather important information from unstructured texts. One of the implications to gaining access to applicant's medical records is to make meaningful inferences from them when a diagnosis is not inherently documented. A deep learning model would have the benefit of targeting certain applicants triggered by ML model for a more careful review without the MEPS provider having to physically read and analyze every applicants EHR.

Zhu et al. (2018), developed a ML model to predict depression severity from analyzing video data. Facial appearance representation as well as facial dynamic changes through time were modeled using deep convolutional neural networks (DCNN). This DCNN model basically feeds two sources of video data, facial appearances, and facial dynamics, which are the changes in facial attributes between frames. Subtle changes in facial features can help detection of depression attributes vs. relying on a single image. Each data source, one utilizing facial appearance and the second using facial dynamic changes, was learned by two separate DCNN models, then combined in a single output prediction. The prediction output, or depression score, was the Beck Depression Inventory-II depression severity, which is clinically recognized. The performance of model was measured by using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The joint model outperformed (MAE 7.58 vs. baseline MAE 10.88) when compared against other models utilizing the same test set (Zhu et al., 2018). Although ML has the possibility for automated screening, from my knowledge, there is no practical model to date that will replace the current medical standards for screening and diagnosis. The MEPS providers, may find a ML tool for depression screening as a helpful aid to help identify which applicants may need additional psychological screening. However, USMEPCOM would need to have access to video files of applicants that would be similar to the data used to the train the model. These are some of the many challenges that would have to be strategized before implementation on widescale use.

Predicting mental health behaviors is important for timely medical intervention and improving patient outcomes and reducing patient suffering. From another perspective, predicting mental health behaviors can be a powerful screening tool for employment suitability or military service. Mental health behaviors are closely linked to the behavioral health conditions that affect military attrition. From straightforward logistic regression to ML algorithms that might be resource intensive, models developed for the purposes of detecting behavior from different data sources have found various degrees of success. Although promising, this area of research is growing and continues to be refined as new methods build upon initial model accuracy. Perhaps the most logical model to pursue would be to pursue a ML model similar to DeepCare from Su et al. (2020), that reads applicants EHR, and makes predictions on future mental health risks. Combining this type of model with the deep neural network model by Geraci et al. (2017), would then be able to make predictions from EHR data where diagnosis were not explicitly stated. Currently, USMEPCOM does not have access to a collective private EHR database. One initial step into the development of model would be to incorporate a private EHR database with its own military legacy system. This would first give a means to validate self-disclosed information. Secondly, it would be the data source to serve the building of deep learning prediction models. Developing a deep learning prediction model is beyond the scope of my research, although it remains an important area for future research.

3. Other Machine Learning Models Used in Military Manpower Analysis Related to Separation

The medical research I discussed includes prediction models using various forms of deep learning complex models. The economic research of prediction models often centers around other machine learning models such as Lasso, random forests, and ensemble methods. This section discusses these other ML models in the context of military separation for broader context and applicability.

ML in economic applications is mostly concerned with returning accurate predicted outcome values. This is different than the traditional parameter estimation models where the focus is on establishing causality (Mullainathan & Spiess, 2017). ML algorithms used for classification of extremely large amount of independent variables is one of its strengths over traditional methods. Instead of hand picking these variables ML searches for meaningful interactions automatically and trains itself to choose them based on hold out samples of the data (Mullainathan & Spiess, 2017). Cole (2020), in a previous NPS thesis researched early service separation of service for both technical and non-technical sailors in the Royal Australian Navy. By using a ML on exit survey data, he aimed to predict attitudes and behaviors for involuntary separation. Linear support vector machines (SVM), random tree, Chi-square automatic interaction detection (CHAID), logistic regression, and K-means models were compared across three data sets for model selection.

Linear SVM models basically are a classification model where the model converts a linear classifier , such as one used to distinguish between a categorical variable, into a non-linear decision boundary. For instance, in order to distinguish the observations into two classes, the model may have to use curved lines to accurately separate them vs. straight lines (James et al., 2013). The linear SVM model predicted early separation with 68.67-72.84% accuracy using predictors that captures sailor's sentiment toward technical and non-technical military careers. Some common themes centered around pay, recognition, and attractiveness of civilian employment (Cole, 2019). Other predictors of importance varied by technical and non-technical sailors with different years of service.

The random tree model is also referred to as random forests. These models build numerous trees on bootstrapped training samples. A bootstrap sample refers to a process that generates new data sets from repeated sampling of an original data set (James et al., 2013). The random tree model builds decision trees by considering the splits/branches from a subset of randomly selected predictors. These variables are randomly selected from the full list of predictors that are supplied to the model. The model is purposefully designed to not consider all predictors at each split. This is done because most trees would have the same strongest predictor at one of the top branches and each tree would be highly correlated. High correlation is not helpful in reducing the variance. The lower the variance when averaging the results of many trees leads to a higher reliability (James et al., 2013). However, the random tree model in Cole's research displayed the most variation in accuracy (41.5%-97.7%) and due to lack of confidence was not selected to as a preferred model to test multiple datasets (Cole, 2019).

The CHAID model is tree based model very similar to the random tree model previously discussed. The difference with CHAID model is the tree splits are based on predictor variables with the smallest p-values. CHAID models also do not hold out variables when determining splits/branches (Diaz-Perez & Bethencourt-Cejas, 2017). In Cole's research, similar to the random tree model, the CHAID model had a wide variation in accuracy (58.4%-89.3%) and due to a lack of confidence was not selected as a preferred model (Cole, 2019).

The K-means model is an unsupervised clustering model. Unsupervised machine learning refers to when there is no measured observation or dependent variable in the data to represent what we want to predict (James et al., 2013). Clustering refers to the process of finding existing subgroups within the observations for which them we can make inferences on. For example, marketing data could use clustering to find subgroups of people to focus advertisements. K-means is a form of clustering that partitions observations so that the variation within the cluster is as small as possible (James et al., 2013). The K-means model in the context of Cole's research, was evaluated based on a silhouette score which ranges from -1 to 1. A value of 1 indicates that the sample of interest is the farthest away from its neighboring clusters, meaning the model has done good job with predicting and dividing the data clusters. The K-means model had very poor silhouette scores of 0.1 (Cole, 2019).

In Cole's work, the SVM model outperformed the other models with consistency of predictors (59.53-91.08%) with less accuracy variation and was chosen as the prediction model (Cole, 2019).

Similarity, in another NPS thesis, Terrazas implemented ML to predict Marine re-enlistment. The data from total force data warehouse and Marine administrative data include various variables such as demographics, performance, recruiting, deployment, legal and re-enlistment incentives. Terrazas (2020 examined 5 ML methods for prediction accuracy: (1) Classification and regression tree (CART), (2) CHAID, (3) Linear SVM, (4) C5 model, and (5) K-means models. Each model performance differed by data set partition and variables included.

The CART model had the overall highest performance utilizing the original dataset with a 50:50 data split for training and test set with an accuracy of 98.84% (Terrazas, 2020). CART is basically a predictive model where the final binary outcome is predicted by the previous branches and forks (James et al., 2013). In this research, the decision tree was utilized to predict the probability that a Marine would re-enlist at the end of any term (classification problem). Tree-based algorithms stratify or segment the sample into multiple branches. The splitting rules used to segment the observations are summarized in a decision tree (James et al., 2013). Each respondent is split into smaller and smaller subgroups based on the independent variables. At the end branches are nodes, which represent the probabilities (classification problem) based on the set of branches that the observation is composed (Speer et al., 2019).

Terrazas found the highest accuracy in prediction using the C5 model (99.54% accurate) with a 50:50 data split that included 64 independent variables (Terrazas, 2020). C5 is another version of a decision tree ML algorithm. After removing the variables associated with separation, the top predictors of re-enlistment associated with the C5 model were the number of deployments, proficiency measures, and conduct issues (Terrazas, 2020).

Another interesting study by Marrone (2020), researched predicting thirty-six-month attrition across all branches of military. Although Marrone did not use ML, they used a probit regression for predicting attrition with approximately 60% accuracy. When the marginal effects of attrition on different characteristics were compared, women were more likely to attrite in the Army vs. other branches, not having a high school diploma were more likely to attrite in the Navy (Marrone, 2020). More importantly, patterns revealed that recruits have different risk periods of higher attrition. Marrone suggest that this may be due to personal characteristics that interact with individual experiences that is not equal across all recruits. This suggests that broad screening policies based on probability of attrition would not be cost effective and potentially screen out too many applicants. Additionally, an accurate prediction for attrition is currently not possible due to not having any data on recruits or applicants detailing observable characteristics that can infer attrition. Most of the data on attrition is ex-post and there needs to be a link from this information to observable characteristics at the time of application (Marrone, 2020). This directly relates to EPS attrition. By linking the pathway from attrition to relevant data at time of recruitment, a predictive model can potentially accurately classify various forms of attrition.

The summation of this and previous chapters answer both my first and second research questions. Implementing ML algorithm to predict separation due to existing prior condition is beyond the scope of my thesis. However, in my empirical portion, I now focus on answering the last research question, which is identifying the mental health risk profile of active-duty service members who attrite before their first term of service. For the purposes of answering this research question, I will be utilizing duration models to provide insights on how certain predictors affect the attrition rates.

V. METHODS

A. DATA SOURCES/SAMPLE POPULATION

The data utilized for this research are de-identified and include quarterly observations of active duty service members from year 2001 to year 2011 obtained from multiple DOD databases. The first dataset is from the Defense Enrolment and Eligibility Reporting System (DEERS) which contains various demographic and service characteristics. The second data source is from the Defense Manpower Data Center which incorporates various service characteristics such as occupation, separation date, etc. In addition, deployment data was incorporated from the Contingency Tracking System. Lastly, DOD health care utilization data from TRICARE was incorporated which includes clinical diagnoses of mental health conditions. The sample population for this study include all enlisted service members from all four (no coast guard?) branches military. The quarter years covered are from 2001 to third quarter of 2011. Fourth quarter of 2011 was incomplete and eliminated from the data. A service member is included in the sample and survival models for the first 24 quarters (6 years) of his career during this study period. A person who is separated from active duty prior to completing 24 quarters of service will have fewer observations. The data contains a total of 2,430,330 unique service members with 30,394,153 person- quarter-year observations.

B. OUTCOME VARIABLES

There are five outcome variables of interest all of which are binary indicator variables. The first outcome is the most straight forward and defined as a general indicator for separation from service for any reason within six years of service. This outcome is the largest with separations. This indicator takes on the value of 1 for a service member on the quarter that he is separated from the military according to the separation file from DMDC, 0 otherwise. Overall, I identified 546,780 enlisted who were separated from the military prior to 24 quarters of service, representing 22% of the sample.

The other four outcomes use different loss codes to categorizes separation due to service members who might be considered unfit for service or EPS condition. To be as transparent as possible, I explain each of these outcomes in detail below.

1. Unfit for Service Separation Outcome

This outcome variable combines a broad category of separation loss codes that are either related to poor conduct, a medical condition, or breaking the law. Basically, if the military member separated for any reason, both major and minor, that is documented by a loss code that can be categorized by poor conduct, a medical condition, or breaking the law, they take on the value of 1 and 0 if otherwise. It contains 31 loss codes out of the 73 possible loss codes. This outcome represents 49,665 separations. See Figure 2 for a complete list of loss codes included.

2. Unfit for Service Separation Due to Major Concerns

This outcome variable represents loss code categories that are related to significant behavior problems. It drops all the soft offenses from the first unfit outcome category. I utilized the same criteria as the unfit outcome but only including those separation codes which could be reasonably deemed as major offenses. The major offenses included are related to significant conduct issues and breaking the law. The soft offenses dropped were discharges related to failure to meet retention requirements, disability, physical fitness/height and weight standards, and the unknown categories. This outcome contains 21 loss codes out of the possible 73 and represents 23,438 separations. See Figure 2 for a complete list of loss codes included in this outcome variable.

3. EPS Only Separation

This outcome is a single loss code for conditions deemed to exist prior to service. The loss codes offer no additional information as to what the condition for separation was. Essentially, this outcome is 1 if a service members separates due to a condition that existed prior to service as determined by the individuals branch of service. This outcome contains 1 loss code out of the possible 73 and represents 207 separations. However, informal conversation with other military analysts indicated that this code might be underutilized.

4. EPS Separation, Combination Category

This outcome combines the EPS separation category with other separation loss codes that are indicative for behavior that would most likely exist prior to service. Some of the separation loss code categories included are: character or behavior disorder, conscientious objector, sexual perversion, etc. This outcome contains 10 loss codes out of the possible 73 and represents 11,278 separations. See Figure 2 for a complete list of loss codes included in this outcome variable.

Loss codes included in each dependent variable				
	Separated, unfit for duty, major and minor categories	Separated, unfit for duty, only major categories	Separated for existed prior to service categories	Separated for existed prior to service combination categories
Loss Code				
AWOL or desertion	X	X		
Alcoholism	X	X		
Breach of contract	X			
Character or behavior disorder	X	X		X
Civil court conviction	X	X		
Commission of a serious offense	X	X		
Condition existing prior to service	X		X	X
Conscientious objector	X			
Court-martial	X	X		
Disability, no condtn existng prior to srvce, no sev pay	X			
Discreditable incidents, civilian or military	X	X		X
Dropped from strength, imprisonment	X	X		
Drugs	X	X		
Entry lev perform and conduct (former Trainee Dschrge Progm)	X			
Failure of course of instruction	X			
Failure to meet minimum qualifications for retention	X			
Failure to meet minimum retention requirements	X			

Figure 2. A list of loss codes included in each dependent variable

Figure 2. A list of loss codes included in each dependent variable (continued)

Loss codes included in each dependent variable				
Failure to meet weight or body fat standards	X			X
Financial Irresponsibility	X	X		
Fraudulent entry	X	X		X
Good of the service (discharge in lieu of court-martial)	X	X		
Misconduct, reason unknown	X	X		
Motivational problems (apathy)	X	X		X
Pattern of minor disciplinary infractions	X	X		X
Sexual perversion	X	X		X
Shirking	X	X		X
Unfitness or unacceptable conduct, other	X	X		
Unqualified for active duty, other	X			X
Unsat performance (former Expeditious Discharge Program)	X	X		
Unsuitability, other	X	X		
Unsuitability, reason unknown	X	X		

C. POTENTIAL PREDICTORS

I included a total of 61 potential predictor variables sub divided into the following 9 categories: Mental health, waivers, stress, deployment, status, service, specialty, demographics, and branch of service. I will discuss each category and associated variable.

1. Mental Health Category

The mental health category includes time varying indicator variables for a diagnosis of self-inflicted injuries (a proxy for a suicide attempt), traumatic stress disorder (PTSD) diagnosis, depression diagnosis, and substance use. The mental health indicators are time varying by current quarter, previous three quarters, or four or more quarters ago.

2. Waiver Category

The waiver category contains 4 indicator variables for the following waivers: minor non-drug related offense waivers, major non-drug related offence waivers, drug waivers, and lastly a category for all other waivers.

3. Stress Category

The stress category includes variables that could cause stress on individuals. These include 6 time varying indicator variables for divorce and rank demotions. The divorce and stress indicators are time varying by current quarter, previous three quarters, or four or more quarters ago.

4. Deployment Category

The deployment category includes three indicator variables for when a service member was deployed that are also time varying by current quarter, previous three quarters, or four or more quarters ago.

5. Status Category

The status category is a single indicator variable for if the individual is in reserve status and not on active duty.

6. AFQT and Service Category

The service category contains the following 10 indicator variables: Missing a AFQT score, AFQT scores in the 0–30 percentile range, AFQT scores in the 31–49 percentile range, AFQT scores in the 50–64 percentile range, AFQT scores in the 65–92 percentile range, and AFQT scores of 93 or above percentile, enlisted members with the rank of E3, enlisted members with rank of E4, enlisted members with rank of E5, and enlisted members with rank of E6.

7. Specialty Category

The specialty category includes the 5 indicator variables that captures if an individual has a combat, support, medical, aviation or other MOS.

8. Demographics Category

The demographics category includes 16 indicator variables. The male variable is a gender indicator variable. There are 6 age group indicator variables. The first age group represents all individuals that are below the age of 22. The second captures those from the age of 22–24. The rest of the age variables continue in this pattern up to age 40 and above. I group four race indicator variables as African American, Hispanic, Asian, and other. The omitted group is White. Additionally, I include an indicator variable for married individuals and include 4 indicator variables for 0–3 numbers of dependents.

9. Branch of Service Category

The last category is a set of 4 indicator variables for each branch of service.

D. STATISTICAL ANALYSIS

For my analysis, I chose a duration model because they are often used to analyze the associated factors that are related to the time it takes for some outcome to occur (Speer et al., 2019). Duration models are also called survival models and hazard models. The hazard models determine the hazard of a certain event happening. For example, in my analysis, the hazard is a military member separating from service within a 6-year window of service. The hazard function is then the probability that the service member separated at interval time *t*, given that they stayed in the military up to time *t* (Hosmer et al., 2008).

The model specification follows that of Shen et al. (2016) and the complete list of variables included were described earlier. The model captures mental health conditions and stressful events, and allows their potential effects on the hazard of separation to vary over time. The ability to capture potential time-varying relationship is important as these variables over time can have different impact on the hazard ratios and can be helpful in understanding the relevant predictors for the hazard (Shen et al., 2016). For these reasons, hazard models can be useful tools in understanding the profile of military members at risk for early separation.

In my analysis, I estimate the hazard rate of each type of separation separately (broad and 5 sub categories), using the Cox proportional hazard model. The 5 sub category separation models represents competing risk models, which represents the risk of that specific type of separation in a specific quarter given that the individual was not separated for any cause in the previous quarter. The time unit is defined as quarter years. An enlisted service member enters the risk window on the first quarter that they joined the military. The individual left the risk window when they separated from the military (1^{st} model) or for a specific reason (2^{nd} to 5^{th} model). All individuals who were not separated from the military for a given separation category by the end of the risk window are right censored. All the models include the same independent variables.

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VI. DESCRIPTIVE STATISTICS

Table 1 displays the frequencies and percentages of the overall sample and the five dependent variables. The overall sample included 2,430,330 unique individuals. The broadest category of separation for any reason within a six year window with 546,780 individuals representing largest portion of separation categories (22.5%). The EPS category represented lowest percent distribution of the sample (0.01%).

Table 1. Frequencies and percentages for overall sample and five dependent variables

Sample	**Unique Individuals**	**By Percentage**
Overall Sample	2,342,491	100.00%
Separated by six year service for any reason	546,780	23.34%
Separated, unfit for duty, major and minor categories	49,665	2.12%
Separated, unfit for duty, only major categories	23,438	1.00%
Separated for existed prior to service category	207	0.01%
Separated for existed prior to service combination categories	11,278	0.48%

The Kaplan Meier survival curve is shown in Figure 3. This curve shows the probability of survival across the span of 24 quarters or 6 years. Additionally, it demonstrates that the Navy has higher rates of survival vs. the other branches.

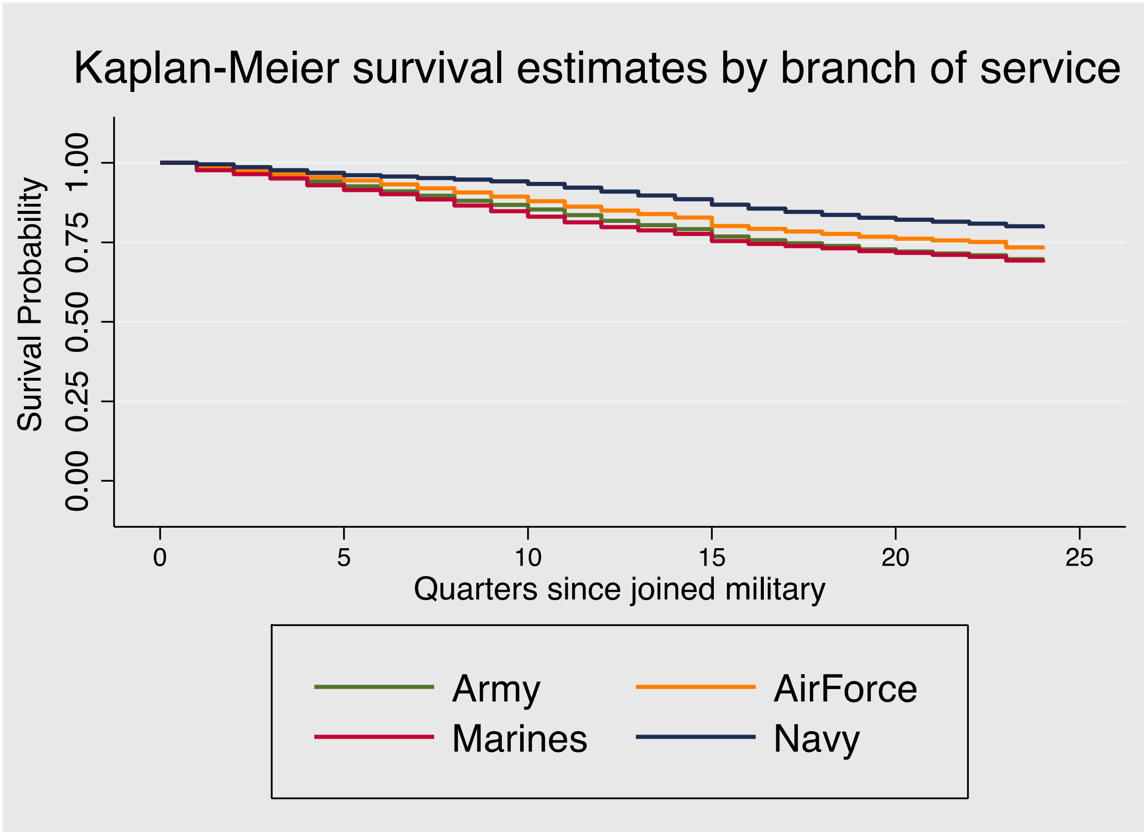

Figure 3. Kaplan-Meier survival estimates by branch of service

Table 2 displays the percent distribution of each predictor variable. The first column shows that the demographic and service characteristics of the sample is representative of the general enlisted population. Among those that were separated within 6 years of service, the Army is overrepresented compared with 48% whereas the Navy had the lowest distribution at 12%. The number of dependents had a significant spread in distribution for those who separated. Having zero dependents represented 72% for those who separated vs. 64% for those were not separated by the end of 6 years of service. Additionally, under the age of 22 and lower in enlisted rank all represented higher distributions for those who separated. Due to low incident rate at the quarterly level, comparing across overall sample and from those who did and did not separated, the percent distribution for the mental health independent variables do not appear to be different. The waiver and the stress category showed some minor variations in the percent distribution across categories.

Table 2. Percent distribution by overall, not separated, and separated

Variable	Overall Sample	Military member did not separate	Separated by six year service for any reason
Mental Health Category			
Self-Inflicted injuries during the current quarter	0.07%	0.06%	0.10%
Self-Inflicted injuries in the previous three quarters	0.11%	0.10%	0.14%
Self-Inflicted injuries four or more quarters ago	0.11%	0.11%	0.07%
Diagnosed PTSD in current quarter	0.21%	0.22%	0.18%
Diagnosed PTSD in previous three quarters	0.54%	0.56%	0.43%
Diagnosed PTSD four or more quarters ago	0.66%	0.72%	0.38%
Diagnosed depression in current quarter	0.19%	0.19%	0.20%
Diagnosed depression in previous three quarters	0.43%	0.43%	0.44%
Diagnosed depression four or more quarters ago	0.49%	0.53%	0.30%
Substance use in the current quarter	0.14%	0.13%	0.15%
Substance use in the previous three quarters	0.31%	0.31%	0.32%
Substance use in the previous four quarters	0.31%	0.33%	0.22%
Waiver Category			
Minor non-drug related offense waiver	0.66%	0.67%	0.60%
Major non-drug related offence waiver	4.08%	4.20%	3.54%
Drug related waiver	1.46%	1.43%	1.58%
Other type of waiver	7.48%	7.67%	6.57%
Stress Category			
Divorced during the current quarter	0.57%	0.60%	0.45%

Variable	Overall Sample	Military member did not separate	Separated by six year service for any reason
Divorced in the previous three quarters	1.23%	1.29%	0.90%
Divorced four or more quarters ago	2.03%	2.22%	1.10%
Demoted in the current quarter	1.10%	1.07%	1.22%
Demoted in the previous three quarters	1.18%	1.19%	1.16%
Demoted four or more quarters ago	1.96%	2.11%	1.23%
<u>Deployment Category</u>			
Deployed during the current quarter	16.26%	16.74%	13.91%
Deployed in the previous three quarters	2.94%	3.05%	2.41%
Deployed in the previous four quarters	17.35%	18.82%	10.24%
<u>Status Category</u>			
In the reserve component	6.73%	7.18%	4.59%
<u>Service Category</u>			
Missing AFQT Score	2.83%	2.97%	2.11%
AFQT Score Categories			
0 -30	4.55%	4.73%	3.69%
31–49	28.11%	28.08%	28.25%
50–64	26.32%	26.25%	26.68%
65–92	35.70%	35.64%	35.96%
93 and above	5.32%	5.31%	5.42%
Enlisted E3	28.45%	27.10%	34.97%
Enlisted E4	33.35%	35.11%	24.85%
Enlisted E5	13.45%	15.14%	5.25%
Enlisted E6	1.87%	2.09%	0.79%
<u>Specialty Category</u>			
Combat MOS	17.50%	17.68%	16.64%
Support MOS	30.18%	30.38%	29.22%
Medical MOS	8.46%	8.66%	7.50%

Variable	Overall Sample	Military member did not separate	Separated by six year service for any reason
Aviation MOS	8.58%	8.72%	7.87%
Other MOS	13.21%	12.50%	16.65%
<u>Demographics</u>			
Male	84.00%	84.01%	83.94%
Age Group			
Under 22	35.92%	33.73%	46.48%
22–24	35.66%	36.77%	30.28%
25–29	19.35%	20.45%	14.07%
30–34	4.73%	5.01%	3.41%
35–39	1.78%	1.87%	1.30%
40 and over	2.56%	2.17%	4.46%
African American	16.52%	16.69%	15.66%
Hispanic	8.23%	8.34%	7.72%
Asian	6.25%	5.84%	8.25%
Other	5.72%	5.89%	4.89%
Married	35.29%	36.71%	28.41%
Number of Dependents			
0	64.99%	63.59%	71.78%
1	16.92%	17.42%	14.50%
2	9.88%	10.30%	7.83%
3	8.21%	8.69%	5.88%
<u>Branch of Service Category</u>			
Army	44.52%	43.88%	47.59%
Air Force	20.39%	20.50%	19.86%
Marine	20.05%	19.89%	20.81%
Navy	15.04%	15.73%	11.74%
N of unique persons	2,342,491		
Number of observations	29,773,714	24,671,293	5,102,421

In a similar comparison, Table 3 shows the percent distribution of the predictor variables used in the model by subcategories of separation. Comparing across the four separation categories, a few variables had more notable but expected differences in distributions. Higher percent of enlisted population that were separated due to EPS received waivers (for minor non-drug related offenses or other reasons) compared to the other 3 separations. Service members who were separated due to any unfit behaviors are more likely to enter the military with drug related waivers (4.3% for any reason and 5% for major reasons) compared to members who were separated due to EPS or EPS related reasons (0 and 0.9%, respectively). Service members who were separated due to major unfit behaviors are more likely to be demoted in previous four quarters (3.5%) compared to other separation categories. The combat MOS had a higher share among those that were separated due to EPS related reasons (20%).

Table 3. Percent distribution by separation category

Variable	Separated by six year service for any reason	Separated, unfit for duty, major and minor categories	Separated, unfit for duty, only major categories	Separated for existed prior to service category	Separated for existed prior to service combination categories
Mental Health Category					
Self-Inflicted injuries during the current quarter	0.10%	0.04%	0.05%	0.06%	0.04%
Self-Inflicted injuries in the previous three quarters	0.14%	0.11%	0.12%	0.17%	0.09%
Self-Inflicted injuries four or more quarters ago	0.07%	0.22%	0.24%	0.00%	0.12%
Diagnosed PTSD in current quarter	0.18%	0.17%	0.20%	0.34%	0.13%
Diagnosed PTSD in previous three quarters	0.43%	0.42%	0.49%	0.84%	0.32%
Diagnosed PTSD four or more quarters ago	0.38%	0.68%	0.78%	0.96%	0.53%
Diagnosed depression in current quarter	0.20%	0.12%	0.13%	0.22%	0.12%
Diagnosed depression in previous three quarters	0.44%	0.27%	0.29%	0.28%	0.29%
Diagnosed depression four or more quarters ago	0.30%	0.46%	0.47%	0.00%	0.48%
Substance use in the current quarter	0.15%	0.17%	0.21%	0.22%	0.11%
Substance use in the previous three quarters	0.32%	0.40%	0.50%	0.56%	0.27%
Substance use in the previous four quarters	0.22%	0.57%	0.70%	0.56%	0.37%

Variable	Separated by six year service for any reason	Separated, unfit for duty, major and minor categories	Separated, unfit for duty, only major categories	Separated for existed prior to service category	Separated for existed prior to service combination categories
Waiver Category					
Minor non-drug related offense waiver	0.60%	0.54%	0.57%	1.29%	0.35%
Major non-drug related offence waiver	3.54%	4.30%	5.02%	3.43%	2.90%
Drug related waiver	1.58%	1.80%	2.15%	0.00%	0.86%
Other type of waiver	6.57%	6.45%	6.04%	10.17%	6.83%
Stress Category					
Divorced during the current quarter	0.45%	0.47%	0.47%	0.56%	0.43%
Divorced in the previous three quarters	0.90%	1.02%	1.01%	1.41%	0.90%
Divorced four or more quarters ago	1.10%	1.70%	1.73%	1.07%	1.45%
Demoted in the current quarter	1.22%	0.92%	1.09%	0.67%	0.70%
Demoted in the previous three quarters	1.16%	1.54%	1.90%	1.41%	1.24%
Demoted four or more quarters ago	1.23%	2.96%	3.52%	2.92%	2.36%
Deployment Category					
Deployed during the current quarter	13.91%	18.02%	18.47%	13.27%	16.35%
Deployed in the previous three quarters	2.41%	2.45%	2.19%	1.52%	2.62%
Deployed in the previous four quarters	10.24%	18.41%	17.68%	11.64%	16.52%

Variable	Separated by six year service for any reason	Separated, unfit for duty, major and minor categories	Separated, unfit for duty, only major categories	Separated for existed prior to service category	Separated for existed prior to service combination categories
Status Category					
In the reserve component	4.59%	3.76%	4.54%	1.85%	2.10%
Service Category					
Missing AFQT Score	2.11%	2.40%	2.52%	1.97%	2.35%
AFQT Score Categories					
0 -30	3.69%	4.65%	5.02%	5.45%	4.21%
31–49	28.25%	32.47%	34.22%	25.46%	28.03%
50–64	26.68%	27.15%	27.39%	27.26%	27.05%
65–92	35.96%	31.77%	29.87%	32.72%	35.30%
93 and above	5.42%	3.97%	3.49%	9.11%	5.40%
Enlisted E3	34.97%	30.41%	30.25%	37.66%	32.63%
Enlisted E4	24.85%	31.38%	29.97%	28.50%	31.10%
Enlisted E5	5.25%	9.71%	8.83%	4.05%	8.36%
Enlisted E6	0.79%	0.56%	0.69%	0.11%	0.24%
Specialty Category					
Combat MOS	16.64%	17.28%	15.93%	17.99%	20.11%
Support MOS	29.22%	30.91%	31.75%	34.85%	29.11%
Medical MOS	7.50%	7.71%	7.73%	8.26%	8.34%
Aviation MOS	7.87%	9.15%	7.84%	9.39%	9.71%
Other MOS	16.65%	11.16%	12.07%	10.06%	11.52%

Variable	Separated by six year service for any reason	Separated, unfit for duty, major and minor categories	Separated, unfit for duty, only major categories	Separated for existed prior to service category	Separated for existed prior to service combination categories
Demographics					
Male	83.94%	90.06%	92.06%	78.30%	85.24%
Age Group					
Under 22	46.48%	40.01%	40.93%	41.65%	42.23%
22–24	30.28%	33.60%	32.24%	31.20%	32.83%
25–29	14.07%	17.67%	17.18%	15.63%	17.08%
30–34	3.41%	3.56%	3.64%	2.87%	3.21%
35–39	1.30%	1.14%	1.28%	1.29%	0.91%
40 and over	4.46%	4.02%	4.72%	7.36%	3.74%
African American	15.66%	21.60%	23.48%	19.62%	18.81%
Hispanic	7.72%	9.10%	8.59%	3.65%	9.06%
Asian	8.25%	8.77%	8.92%	8.15%	9.50%
Other	4.89%	5.16%	4.69%	3.49%	5.96%
Married	28.41%	36.30%	36.13%	34.01%	34.41%
Number of Dependents					
0	71.78%	62.23%	62.14%	62.79%	64.44%
1	14.50%	17.31%	16.93%	14.84%	17.41%
2	7.83%	11.29%	11.35%	12.48%	10.38%
3	5.88%	9.17%	9.59%	9.89%	7.77%
Branch of Service Category					
Army	47.59%	49.04%	54.60%	46.60%	47.12%
Air Force	19.86%	14.68%	14.36%	23.72%	18.98%
Marine	20.81%	18.44%	16.47%	16.13%	9.43%

Variable	Separated by six year service for any reason	Separated, unfit for duty, major and minor categories	Separated, unfit for duty, only major categories	Separated for existed prior to service category	Separated for existed prior to service combination categories
Navy	11.74%	17.84%	14.57%	13.55%	24.47%
N of unique persons	2,342,491				
Number of observations	5,102,421	571,430	381,664	1,779	169,427

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VII. RESULTS

I present the results of the proportional hazard models in Table 4. The first column shows the hazard ratios and corresponding standard errors for the broadest outcome—separation due to any reasons. The next 3 columns show the results from the competing risk models for each of the three sub categories of separation. Due to having too few separations that were classified in the EPS only category, I was not able to obtain model convergence on this outcome and therefore it is excluded from Table 4.

The first panel shows the relationship between the following mental health diagnoses and separation: self-inflicted injuries (as a proxy for suicide attempts), PTSD, major depression, and substance misuse disorder. Table 4 shows that substance use disorder is positively associated with separation. Take the first column as an example, those who had substance use disorder in the previous 3 or previous 4 quarters has a 1.15 and 1.23 higher hazard, respectively, of separating from the military compared to service members who did not have substance use disorder in the current quarter. When breaking down the separation categories, we also observe this relationship for separation due to unfit behaviors where the strongest relationship is for separation due to major unfit behaviors (2nd and 3rd column of Table 4). The HRs are much higher at 3.37 and 3.84 respectively. Meaning, those who had a substance use disorder in the previous 4 quarters were 3.84 times as likely to be separated due to unfit reasons vs. those who did not have a substance use disorder. We observe a statistically significant relationship between depression and separation. Those who were diagnosed with major depression in the previous 3 quarters is 1.19 times more likely to be separated from the service than a service member who never had depression diagnosis during the study period. Self-Inflicted injuries 4 or more quarters ago is statically significant and associated with a higher hazard ratio for separation for unfit and EPS combination categories (2nd, 3rd , and 4th columns of Table 4). The strongest relationship between past suicide attempts and separation is observed in the last column for EPS combination categories with a HR of 2.22, meaning, those who had self-inflicted injuries four or more quarters ago, were 2.22 times more likely to separate for an EPS related behaviors.

Consistent with the mental health diagnoses panel, I find that the hazard of unfit for duty separations from the military within 6 years are 1.3 times higher for those receiving drug waivers to enter the military compared to those without any waivers. This relationship is mainly observed in separation due to unfit behaviors and not due to EPS related behaviors. Interestingly, reverse of my expectations, both major offence waiver and minor offence waiver are both associated with lower hazard ratios of separating across all modeled separation outcomes.

In the third panel, I find that divorce is associated with a lower risk of separation. This is true across all models of separation categories. Although this seems counterintuitive, it suggests that once the decision to divorce has been made, it has less of an effect on separations. Also in the stress category, I find being demoted 4 or more quarters ago is associated with a higher separation rate due to unfit for duty (HR=1.72). Current quarter demotions have a lower risk of separation, possibly because the individuals that are more at risk for separating are those who have attitudes, skills, and job performance attributes that are highly employable in the civilian labor market. Thus, a current demotion leaves little options for civilian opportunities and individuals choose to stay to clear performance records for future applicable opportunities.

In the fourth panel I find that deployments have a mixed effect on separation. The hazard of separating from the military within 6 years for major unfit reasons are 1.36 times higher for those who are currently deployed compared to those who did not deploy in the same quarter. For EPS combination separations, the hazard rate is higher for those who deployed 4 or more quarters ago (HR=1.86) vs. current quarter deployment (HR=1.34). This trend carries across all of the separation outcomes. The higher separation hazard for deployment 4 or more quarters ago could possibly be due to an individual's sentiment for service that occurs after deployments. It may also be possibly due to readjustment issues.

In the service panel, I find that a higher hazard of separation is associated with a service member that has a missing armed forces qualification test (AFQT) score. The hazard ratios (HRs) for missing an AFQT score across the 4 different outcomes were the highest for the 3rd model (HR 3.13) meaning that those service members who were missing a AFQT score, are 3 times as likely to be separated due to a major unfit for duty category, compared to those who did not have a missing AFQT score. Due to the uncertainty of why the AFQT score is missing from the data, it is not plausible for further interpretation. Additionally, I find that risk of separating from the military within 6 years is the lowest for the enlisted rank of E6 (HR=0.21). This could be potentially due to the job satisfaction and the approach of retirement as a military member reaches higher pay grades and ranks.

In the MOS category, I find that in the EPS combination loss code separation outcome, the combat, support and aviation MOS variables are associated with a higher hazard ratio for separation at HR 1.13, 1.17, 1.13 respectively. However, this changes when compared to other separation categories where there is a lowered risk separation. The increased hazard ratio could be due to the cumulative effects of stress and lifestyle of combat MOS that aggravates behavioral and mental health conditions that existed prior to service but were never diagnosed or identified. This would then lead to a higher rate of separation for these individuals.

In the demographics panel, I find that the males have a higher hazard rate of separation for unfit for duty separations (HR 2.35) compared to females. Male service members are 2.35 times as likely to be separated due to an unfit for duty major loss code category, compared to females. For the age categories, I find the age group of 35–39 has a higher hazard rate of separation from military within 6 years of service (HR=1.17) compared to the under 22 age group. Consistent with expectations, the 40 and over age group is associated with the highest rates of separation across all models. Additionally, having 1 dependent is associated with a lower HR of separation within 6 years of service (HR=0.98), alternatively this is opposite for the EPS combination separations for which the hazard ratio is higher (HR=1.21) for those who have one dependent compared to those who have no dependents. In addition, after controlling for all the other behavioral and service characteristics, I observe that African American enlisted service members have a higher hazard of being separated in the unfit category (HR=1.62) compared to other ethnic groups. Additionally, the Hispanic enlisted service members have a higher separation rate across all models compared to other ethnic groups. Although I must exhibit extreme caution that this cannot be taken as a direct interpretation. It is unclear and the data does not indicate any causal relationship. This should not be interpreted at face value due to the many complicated contributing factors that are associated with race and reasons for separation. Further investigation is warranted to better understand these differences.

In the final panel, I observe that the Navy, Marines, and Air Force all exhibit lower HRs of separation compared to the Army for all separation outcomes.

Table 4. Separation by category and associated hazard ratios for each potential predictor variable

Potential Predictor Variables	**Separated by six year service for any reason** Hazard Ratio	se	**Separated, unfit for duty, major and minor categories** Hazard Ratio	se	**Separated, unfit for duty, only major categories** Hazard Ratio	se	**Separated for existed prior to service combination categories** Hazard Ratio	se
Mental Health Category								
Self-Inflicted injuries during the current quarter	0.92+	(0.04)	0.50**	(0.12)	0.62*	(0.15)	0.66	(0.23)
Self-Inflicted injuries in the previous three quarters	1.07+	(0.04)	0.97	(0.15)	0.91	(0.16)	1.02	(0.27)
Self-Inflicted injuries four or more quarters ago	1.06	(0.04)	1.90**	(0.27)	1.90**	(0.30)	2.22**	(0.54)
Diagnosed PTSD in current quarter	0.82**	(0.03)	0.67**	(0.10)	0.72*	(0.12)	0.61+	(0.17)
Diagnosed PTSD in previous three quarters	0.88**	(0.02)	0.76**	(0.07)	0.81*	(0.09)	0.75	(0.13)
Diagnosed PTSD four or more quarters ago	0.91**	(0.02)	0.94	(0.09)	1.05	(0.10)	0.84	(0.15)
Diagnosed depression in current quarter	1.05+	(0.03)	0.76+	(0.11)	0.79	(0.12)	0.84	(0.19)
Diagnosed depression in previous three quarters	1.19**	(0.02)	0.87	(0.09)	0.87	(0.10)	0.9	(0.15)
Diagnosed depression four or more quarters ago	1.01	(0.02)	1.17	(0.12)	1.15	(0.13)	1.25	(0.22)
Substance use in the current quarter	1.06	(0.04)	1.53**	(0.18)	1.85**	(0.23)	0.75	(0.22)
Substance use in the previous three quarters	1.15**	(0.03)	1.76**	(0.14)	1.94**	(0.17)	1.33+	(0.22)
Substance use in the previous four quarters	1.23**	(0.03)	3.37**	(0.25)	3.84**	(0.30)	2.56**	(0.39)

Potential Predictor Variables	Separated by six year service for any reason Hazard Ratio	se	Separated, unfit for duty, major and minor categories Hazard Ratio	se	Separated, unfit for duty, only major categories Hazard Ratio	se	Separated for existed prior to service combination categories Hazard Ratio	se
Waiver Category								
Minor non-drug related offense waiver	0.86**	(0.02)	0.63**	(0.06)	0.70**	(0.07)	0.44**	(0.09)
Major non-drug related offence waiver	0.74**	(0.01)	0.40**	(0.02)	0.49**	(0.02)	0.23**	(0.02)
Drug related waiver	1.03**	(0.01)	1.23**	(0.05)	1.30**	(0.06)	0.74**	(0.08)
Other type of waiver	0.82**	(0.00)	0.59**	(0.02)	0.56**	(0.02)	0.67**	(0.03)
Stress Category								
Divorced during the current quarter	0.65**	(0.01)	0.49**	(0.06)	0.46**	(0.06)	0.44**	(0.09)
Divorced in the previous three quarters	1.01	(0.01)	0.87+	(0.06)	0.88	(0.08)	0.83	(0.10)
Divorced four or more quarters ago	0.91**	(0.01)	0.74**	(0.05)	0.76**	(0.06)	0.84	(0.10)
Demoted in the current quarter	0.93**	(0.01)	0.64**	(0.04)	0.70**	(0.04)	0.69**	(0.08)
Demoted in the previous three quarters	0.90**	(0.01)	1.07	(0.05)	1.26**	(0.07)	0.92	(0.08)
Demoted four or more quarters ago	0.92**	(0.01)	1.44**	(0.06)	1.72**	(0.08)	1.08	(0.10)
Deployment Category								
Deployed during the current quarter	1.15**	(0.00)	1.35**	(0.02)	1.36**	(0.03)	1.34**	(0.04)
Deployed in the previous three quarters	1.13**	(0.01)	0.94	(0.04)	0.91+	(0.05)	1.07	(0.08)

Potential Predictor Variables	Separated by six year service for any reason Hazard Ratio	se	Separated, unfit for duty, major and minor categories Hazard Ratio	se	Separated, unfit for duty, only major categories Hazard Ratio	se	Separated for existed prior to service combination categories Hazard Ratio	se
Deployed in the previous four quarters	1.33**	(0.01)	2.02**	(0.04)	2.00**	(0.05)	1.86**	(0.07)
Status Category								
In the reserve component	0.30**	(0.00)	0.22**	(0.01)	0.26**	(0.01)	0.05**	(0.00)
Service Category								
Missing AFQT Score	1.26**	(0.02)	3.01**	(0.19)	3.13**	(0.23)	2.14**	(0.26)
AFQT Score By Percentiles Categories								
0 -30	1		1		1		1	
31–49	1.36**	(0.02)	2.04**	(0.11)	2.07**	(0.13)	2.08**	(0.21)
50–64	1.40**	(0.02)	2.15**	(0.12)	2.14**	(0.13)	2.43**	(0.24)
65–92	1.47**	(0.02)	2.14**	(0.12)	2.01**	(0.13)	2.58**	(0.26)
93 and above	1.64**	(0.02)	2.09**	(0.13)	1.74**	(0.12)	3.02**	(0.32)
Enlisted E3	0.95**	(0.00)	0.95**	(0.02)	0.89**	(0.02)	1.25**	(0.03)
Enlisted E4	0.61**	(0.00)	0.49**	(0.01)	0.47**	(0.01)	0.63**	(0.02)
Enlisted E5	0.38**	(0.00)	0.14**	(0.01)	0.13**	(0.01)	0.19**	(0.02)
Enlisted E6	0.21**	(0.00)	0.01**	(0.00)	0.01**	(0.00)	0.02**	(0.01)
Specialty Category								
Combat MOS	0.98**	(0.00)	0.92**	(0.02)	0.83**	(0.02)	1.13**	(0.04)
Support MOS	0.98**	(0.00)	1.04**	(0.02)	1.01	(0.02)	1.17**	(0.03)

Potential Predictor Variables	Separated by six year service for any reason Hazard Ratio	se	Separated, unfit for duty, major and minor categories Hazard Ratio	se	Separated, unfit for duty, only major categories Hazard Ratio	se	Separated for existed prior to service combination categories Hazard Ratio	se
Medical MOS	0.84**	(0.01)	0.64**	(0.02)	0.58**	(0.02)	0.78**	(0.03)
Aviation MOS	0.94**	(0.01)	0.85**	(0.02)	0.79**	(0.03)	1.13**	(0.05)
Other MOS	1.11**	(0.01)	0.79**	(0.02)	0.79**	(0.02)	0.77**	(0.03)
Demographics								
Male	0.99	(0.00)	1.78**	(0.04)	2.35**	(0.06)	1.22**	(0.04)
Age Group								
Under 22	1		1		1		1	
22–24	0.92**	(0.00)	0.86**	(0.01)	0.82**	(0.02)	0.84**	(0.02)
25–29	0.92**	(0.00)	0.88**	(0.02)	0.82**	(0.02)	0.83**	(0.03)
30–34	0.98*	(0.01)	0.80**	(0.03)	0.76**	(0.04)	0.70**	(0.05)
35–39	1.17**	(0.02)	0.9	(0.07)	0.80*	(0.07)	0.78+	(0.10)
40 and over	5.21**	(0.03)	14.05**	(0.26)	13.68**	(0.29)	15.19**	(0.47)
African American	0.93**	(0.00)	1.38**	(0.02)	1.62**	(0.03)	1.16**	(0.03)
Hispanic	1.09**	(0.01)	1.22**	(0.03)	1.22**	(0.03)	1.24**	(0.04)
Asian	0.76**	(0.01)	0.29**	(0.01)	0.29**	(0.01)	0.33**	(0.02)
Other	0.96**	(0.01)	1.09**	(0.03)	1.04	(0.04)	1.23**	(0.05)
Married	0.99+	(0.01)	0.96+	(0.02)	0.93**	(0.03)	0.96	(0.04)
Number of Dependents								
0	1		1		1		1	
1	0.98**	(0.01)	1.09**	(0.03)	1.08**	(0.03)	1.21**	(0.05)
2	0.90**	(0.01)	1.08**	(0.03)	1.10**	(0.04)	1.17**	(0.06)

Potential Predictor Variables	Separated by six year service for any reason Hazard Ratio	se	Separated, unfit for duty, major and minor categories Hazard Ratio	se	Separated, unfit for duty, only major categories Hazard Ratio	se	Separated for existed prior to service combination categories Hazard Ratio	se
3	0.82**	(0.01)	0.88**	(0.03)	0.93+	(0.04)	0.86**	(0.05)
Branch of Service Category								
Army	1		1		1		1	
Air Force	0.76**	(0.00)	0.63**	(0.01)	0.77**	(0.02)	0.70**	(0.02)
Marine	0.91**	(0.00)	0.73**	(0.01)	0.87**	(0.02)	0.48**	(0.01)
Navy	0.73**	(0.00)	0.59**	(0.01)	0.49**	(0.01)	0.83**	(0.03)
N of unique persons	2,342,491							
Number of observations	28336896		28662810		28662812		28662814	

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VIII. SUMMARY

RECOMMENDATIONS/CONCLUSION

In my analysis, I estimated the hazard rates of separating from the military within 6 year of service using the Cox proportional hazard model on 4 separation outcomes (overall and 3 sub categories). Factors that are associated with higher hazard of separations include past self-inflicted injuries, substance use disorder (current and in the past), waivers for drug offenses, those with missing AFQT scores, and deployments (current and in the past). The drug related factors are associated with higher hazard of separation due to unfit behaviors and EPS related behaviors.

While this empirical exercise is not a direct application of prediction models to screen applicants, the information provides insights and knowledge regarding the separation risks associated with various indicators. Although a broad profiling tool is unlikely to be generated from this data, is does show differences in various variables do exist depending on the separation category. USMEPCOM has a rigorous AFQT testing program. It is unclear from the data that if the missing AFQT score is due to allowing applicants to enter without a score, or if the score is missing from their data. Perhaps continuing to focus on screening qualified applicants corresponding to AFQT scores as well as identifying and evaluating applicants with missing scores will provide an insight into early separations. Identifying applicants at risk for substance use early in the application period is a valuable screening tool. Waivers for drug offenses may be related to the substance use. For those that already have expressed a behavior that is indicative of substance use (drug waiver), their behavior may continue in the future leading to early separation. Additionally, the higher hazard of separation among Black and Hispanic enlisted members warrants follow up analysis to understand what the contributing factors may be. Further analysis is needed to understand the complex issues regarding race and separation.

In addition to the insights on applicant profiling provided by this data, the literature review also provides insights. The screening processes of the insurance industry and MEPS are similar in that they both require self-disclosure. USMEPCOM may consider continuing to search for a means to include validated medical history as part of the medical screening. The conducted pilot program obtaining access to the PRMRS provided a means to reconcile applicants self-disclosed information to their medication history. Continuing to use this information would be greatly beneficial for MEPS providers acting similarly to an actuary having access to the MIB. Access to validated data will be important to safeguard against EPS conditions. However, reviewing this information can be a very time-consuming process and not realistically feasible given the sheer volumes of applicants processed each day. This is where further analysis and development is needed to create an EPS medical attrition predictive model, incorporating applicant's prescription and other medical history. Perhaps the most logical model to develop would be to pursue a ML model similar to DeepCare from Su et al. (2020), that reads applicants EHR, and makes predictions on future mental health risks. Combining this type of model with the deep neural network model by Geraci et al. (2017), would improve the model to make predictions from EHR data where diagnosis were not explicitly stated. One important aspect to building a DCNN is that it needs to be trained with the data that is most relevant to the prediction population. This may be an issue for USMEPCOM since the data available is most likely from current service members and not potential military applicants, meaning there would be a miss-match in the data source to serve the building of DCNN prediction model. The comprehensive medical screening by MEPS is not likely to be replaced by an analytical model. Instead, an analytical model may provide valuable information to be used in conjunction with the existing process.

I began my research seeking to answer these three research questions related to the issue of identifying non-disclosed EPS conditions early in the medical screening for potential applicants. Through my literature review, I identified the current practice to identify pre-existing conditions in the civilian insurance sector. I also explored relevant prediction models in the economic, actuary and medical fields that have benefit applications in military medical accession screening. Lastly, through a statistical analysis using a Cox proportional model, various predictor variables were shown to have an increased hazard ratio for separations leading to a starting base for further risk profiling research. With the modest contributions of my research, and further future research, I am hopeful that statistical models along with traditional medical screening methods will provide an important step in preventing early separations and accurately predicting and screening for pre-existing conditions in military applicants.

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APPENDIX. MEDICAL SCREENING FORMS

MEDICAL PRESCREEN OF MEDICAL HISTORY REPORT
(Chapter #2 Physicals Only)

OMB No. 0704-0413
OMB approval expires
Oct 31, 2006

The public reporting burden for this collection of information is estimated to average 10 minutes per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing the burden, to the Department of Defense, Executive Services Directorate (0704-0413). Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to any penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.

PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ORGANIZATION. RETURN COMPLETED FORM AS INDICATED ON PAGE 2.

PRIVACY ACT STATEMENT

AUTHORITY: 10 USC 504, 505, 507, 532, 978, 1201, 1202, and 4346; and E.O. 9397 (SSAN).
PRINCIPAL PURPOSE(S): To obtain medical data for determination of medical fitness for enlistment, induction, appointment and retention for applicants and members of the Armed Forces. The information will also be used for medical boards and separation of Service members from the Armed Forces.
ROUTINE USE(S): None.
DISCLOSURE: Voluntary; however, failure by an applicant to provide the information may result in delay or possible rejection of the individual's application to enter the Armed Forces. For an Armed Forces member, failure to provide the information may result in the individual being placed in a non-deployable status.

WARNING: The information you have given constitutes an official statement. Federal law provides severe penalties (up to 5 years confinement or a $10,000 fine or both), to anyone making a false statement. If you are selected for enlistment, commission, or entrance into a commissioning program based on a false statement, you can be tried by military courts-martial or meet an administrative board for discharge and could receive a less than honorable discharge that would affect your future.

1. APPLICANT

a. LAST NAME - FIRST NAME - MIDDLE INITIAL (SUFFIX)	b. DATE OF BIRTH *(YYYYMMDD)*	c. SOCIAL SECURITY NUMBER

d. HEIGHT	e. WEIGHT	f. MAXIMUM WEIGHT	g. SERVICE/COMPONENT			h. DATE SCREENED *(YYYYMMDD)*
			ARMY	USMC	REGULAR	
				USCG	RESERVE	
	lbs.		NAVY	USAF	NATIONAL GUARD	

2. Mark each item "YES" or "NO". Every item marked "YES" must be fully explained in Item 2b.

a. HAVE YOU EVER HAD OR DO YOU NOW HAVE:	YES	NO		YES	NO
(1) Asthma, wheezing, or inhaler use (4)			(24) Any other heart problems (4)		
(2) Dislocated joint, including knee, hip, shoulder, elbow, ankle or other joint (1)(7)			(25) High blood pressure (4)		
(3) Epilepsy, fits, seizures, or convulsions (4)			(26) Discharged from military service for medical reasons (4)		
(4) Sleepwalking (4)			(27) Ulcer *(stomach, duodenum or other part of intestine)* (4)		
(5) Recurrent neck or back pain (4)(1)(7)			(28) Received disability compensation for an injury or other medical condition (4)		
(6) Rheumatic fever (4)			(29) Hepatitis *(liver infection or inflammation)* (4)		
(7) Foot pain (3)			(30) Intestinal obstruction *(locked bowels)*, or any other chronic or recurrent intestinal problem, including small intestine or colon problems, such as Crohn's disease or colitis (4)		
(8) A swollen, painful, or dislocated joint or fluid in a joint *(knee, shoulder, wrist, elbow, etc.)* (1)(7)			(31) Detached retina or surgery for a detached retina (4)		
(9) Double vision (4)			(32) Surgery to remove a portion of the intestine *(other than the appendix)* (4)		
(10) Periods of unconsciousness (4)			(33) Any other eye condition, injury or surgery (4)		
(11) Frequent or severe headaches causing loss of time from work or school or taking medication to prevent frequent or severe headaches (4)			(34) Are you over 40? *(If so, call the MEPS for information on special requirements for over-40 physicals)* (4)		
(12) Wear contact lenses *(If so, bring your contact lens kit and solution so you can remove your contact when we test your vision at the MEPS; also, if you have a pair of eyeglasses, bring them with you no matter how old they are.)*			(35) Gall bladder trouble or gall stones (4)		
(13) Fainting spells or passing out (4)			(36) Jaundice (4)		
(14) Head injury, including skull fracture, resulting in concussion, loss of consciousness, headaches, etc. (4)			(37) Missing a kidney (4)		
(15) Back surgery (4)			(38) Allergy to common food *(milk, bread, eggs, meat, fish or other common food)* (4)		
(16) Seen a psychiatrist, psychologist, social worker, counselor or other professional for any reason *(inpatient or outpatient)* including counseling or treatment for school, adjustment, family, marriage or any other problem, to include depression, or treatment for alcohol, drug or substance abuse (6)(2)			(39) *(Females only)* Abnormal PAP smear or gynecological problem (4)		
(17) Any of the following skin diseases:			(40) *(Males only)* Missing a testicle, testicular implant, or undescended testicle (4)		
(a) Eczema (5)			(41) Broken bone requiring surgery to repair *(with or without pins, plates, screws or other metal fixation devices used in repair)*		
(b) Psoriasis (5)			(42) Ruptured or bulging disk in your back or surgery for a ruptured or bulging disk (4)		
(c) Atopic dermatitis (5)			(43) Thyroid condition or take medication for your thyroid (4)		
(18) Irregular heartbeat, including abnormally rapid or slow heart rates (4)			(44) Limitation of motion of any joint, including knee, shoulder, wrist, elbow, hip or other joint (4)(1)(7)		
(19) Allergic to bee, wasp, or other insect stings *(itching/swelling all over and/or get short of breath)* (4)			(45) Drug or alcohol rehab (4)		
(20) Heart murmur, valve problem or mitral valve prolapse (4)			(46) Kidney, urinary tract or bladder problems, surgery, stones or other urinary tract problems (4)		
(21) Allergic to wool (4)			(47) Sugar, protein or blood in urine (4)		
(22) Heart surgery (4)			(48) Surgery on a bone or joint *(knee, shoulder, elbow, wrist, etc.)* including Arthroscopy with normal findings (1)(7)		
(23) Been rejected for military service *(temporary or permanent)* for medical or other reasons (4)			(49) Taking any medications *(If so, list reason in item 2b.)*		

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MEDICAL PRESCREEN

LAST NAME - FIRST NAME - MIDDLE INITIAL (SUFFIX)	SOCIAL SECURITY NUMBER

2a. *(Continued)* HAVE YOU EVER HAD OR DO YOU NOW HAVE:	YES	NO		YES	NO
(50) Pain or swelling at the site of an old fracture (4)(1)(7)			(64) Shoulder, knee, or elbow problem *(out of place)* (4)(1)(7)		
(51) Perforated ear drum or tubes in ear drum(s) (4)			(65) Locking of the knee or other joint (4)(1)(7)		
(52) Anemia (4)			(66) Giving way of knee or other joint (4)(1)(7)		
(53) Ear surgery, to include mastoidectomy or repair of perforated ear drum, hearing loss or need/use a hearing aid (4)			(67) Cataracts or surgery for cataracts (4)		
(54) Night blindness (4)			(68) Eye surgery, including radial keratotomy, lens implant or other eye surgery to improve your vision (4)		
(55) Arthritis (4)			(69) Collapsed lung or other lung condition (4)		
(56) Absence or disturbance of the sense of smell (4)			(70) Bed wetting since age 12 (4)		
(57) Absence or removal of the spleen, or rupture or tear of the spleen without removal (4)			(71) Evaluation, treatment, or hospitalization for alcohol abuse, dependence, or addiction (4)(6)		
(58) Anorexia or other eating disorder (4)			(72) Taken medication, drugs, or any substance to improve attention, behavior, or physical performance (2)(1)(6)		
(59) Cracked bone or fracture(s) (4)					
(60) Bursitis (4)			(73) Do you smoke? *(If yes:)*		
(61) Braces *(If you wear or are planning on obtaining braces for your teeth, have the orthodontist submit a letter stating that braces will be removed before active duty date; release form and sample format can be found in the Recruiter's Medical Guide.)*			(a) Type ☐ Cigarettes ☐ Cigars ☐ Smokeless tobacco (b) How many per day? (c) Date last used		
(62) Loss of finger, toe or part thereof (4)			(74) Evaluation, treatment, or hospitalization for substance use, abuse, addiction or dependence *(including illegal drugs, prescription medications, or other substances)*		
(63) Loss of the ability to fully flex *(bend)* or fully extend a finger, toe or other joint (4)(1)(7)			(75) Any illnesses, surgery, or hospitalization not listed above		

b. **EXPLAIN ALL "YES" ANSWERS TO QUESTIONS (1) - (75) ABOVE.** *(Describe answer(s), give date(s) of problems, name doctor(s), clinic(s), hospital(s), treatment given and current medical status. Attach additional sheet(s) if necessary.)*

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